The Influence of information quality on e-channel choice: Investigating moderating effects of Product types and Gender

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THE INFLUENCE OF INFORMATION QUALITY ON E-CHANNEL CHOICE:
INVESTIGATING MODERATING EFFECTS OF PRODUCT TYPES AND GENDER

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ABSTRACT
Online consumers are faced with uncertainty as they purchase products without personally experiencing them for themselves, such as through touching, trying on, etc. With the rapid development of web technologies, much of this experience can now be substituted by online tools that provide information through 3-D images, sound clips, and customization tools. We investigated to see whether provided by online tools can accommodate personal evaluation of products the same way across different types of products and gender. To test this moderation effects, we used Lim et al.’s (2012) research model, specifically on the causal relationship between perceived information quality and its determinants. Using EQS 6.1, we ran structural equation modeling (SEM) and Lagrange Multiplier Test (LM Test) to test the sample data of 309 participants.

Keywords
Information quality, moderation, gender difference, experience attributes, SEM, LM Test

INTRODUCTION
The popularity of smart phones, tablets, and smart TV’s has brought e-commerce markets into consumers’ homes. People choose e-channels over physical stores not only to seek information, but also to purchase products (Brown and Dant, 2014; Stone, 2011). Researchers have come up with numerous explanations for the status quo of the e-commerce market, but we note on the quality of product information, which is supposed to substitute in-person consumer experience and accommodate consumers’ evaluation of products and service. Lim, Grover, and Purvis (2012) focused on factors enhancing information quality, which enables consumers’ choice of electronic channels for purchase. However, some products might sell more easily than others on the e-commerce websites, and someone of a different gender might perceive the same information differently. This leads us to investigate if there is any product-type or gender bias in perceiving and accepting information on the Web, which leads to channel choice. To start this discussion, we first review Lim et al.’s (2012) model for information quality as the base for our research model in the next section. To offer theoretical framework for our model, we review the literature about product characteristics and the mechanism through which websites communicate these characteristics to consumers in the next section. Then, our research model will be introduced, followed by research methods, data analysis, and conclusion.

E-CHANNEL CHOICE MODEL OF LIM ET AL.
Lit et al (2012) attempt to find out what determine consumers’ choice of e-channels for purchasing products. They specifically note on performance risk as a relevant type of risk in the e-commerce context since the risk has been known to be the bottleneck that deters the development of e-commerce. Performance risk is concerned with whether a purchased product will perform as expected and satisfy the consumers’ requirements (Nöteberg, Christiaanse, and Wallage, 2003). Lim et al. (2012) further draw on media richness theory to identify factors that reduce uncertainty and equivocality, which eventually reduce the perceived performance risk. Their solution to reduce uncertainty and equivocality is through communicating rich information with online consumers. With high quality information, consumers can substitute product experience with information provided online as seen Lim et al.’s (2012) model (Figure 1). Their model proves that online consumers perceive higher information quality when (1) the website portrays a physical environment mediated through the Internet (Telepresence), (2) the website provides various search agents (Screening capability), (3) the website shows clean and organized information without imposing overhead (Cognitive overhead), and (4) the website has a good reputation and is trustable (Channel trustworthiness).
**Construct** | **Definition**
---|---
Choice of E-Channels | A consumer’s decision to use e-channels as a purchasing place beyond an information source, substituting physical channels.
Information Quality in E-Channels | The degree to which the information facilitates consumers’ evaluation of products to complete the purchasing tasks.
Telepresence | The extent to which one can experience one’s physical environments through the mediation of the Internet.
Screening Capability | The ability of the search agent to sort and filter the vast amount of information based on the given criteria.
Cognitive Overhead | The amount of mental activity imposed on a person’s working memory at an instance in time before processing a main task of information search.
Channel Trustworthiness | Beliefs about web stores comprising a willingness to become vulnerable to that store.

*Table 1. Definitions of Constructs in Lim et al.’s Model*

**PRODUCT CHARACTERISTICS AND INFORMATION**

To understand the information required for product evaluation and experience, different characteristics of products need to be considered. Categorizing products according to their characteristics has a significant meaning in the study of information quality in the e-commerce context. It helps examine how consumers comprehend product information and judge the value and quality of a product (Sujan and Dekleva, 1987; Meyers-Levy and Tybout, 1989). There have been a number of categorization schemas for products in the marketing literature (Hepp, Leukel, and Schmitz, 2007; Peterson et al., 1997) such as high-low value, degree of perishability (Berman, 1996), frequency and size of purchase (Black, Lockett, Ennew, Winklhofer, and McKechnie, 2002). Among these, Nelson’s (1970, 1974) categorization by the experience/search attributes of goods seems to be especially relevant for the current research dealing with consumers’ behaviors since the categorization is based on consumer perception.

Using the attributes of products as a criterion, Nelson (1970, 1974) distinguishes between search goods and experience goods. Nelson declares a good as a search good if full information about the quality and value can be obtained before consumers buy and use it, while an experience good is one of which quality and value are difficult to evaluate until
consumers purchase and use it. Three-hole binders and books are popular examples of search goods in the literature. Consumers do not need to experience search goods before they decide to purchase them. A good example for an experience good is a car. A consumer would want to test-drive a car before she makes the decision to buy one. This classification of goods represents a spectrum of experience and search attributes of a product rather than a distinctive unit of each types of attributes. Consequently, Klein (1998) defines an experience good as one that is “dominated by attributes for which information search is more costly and/or difficult than direct product experience”. Therefore, every product can be said to have some extent of both experience and search attributes (Shapiro and Varian, 1999), and a product would be called an experience good only if it is believed to have more experience attributes than search attributes. Another type of good in terms of experience attributes is referred to as a credence good that possesses credence attributes. A product is a credence good if it is too costly, if not impossible, to evaluate its quality even after consumers use the product (Darby and Karni, 1973). Vitamin supplements, medical service and car repair service are well-known credence goods. For example, an average customer of the car repair service would not be able to evaluate whether a removal or a replacement of a part was appropriate or not (Hahn, 1998). Since credence goods are mostly services, they will not be further considered in this dissertation.

In the literature, experience goods are known to demand physical examination and are not particularly suitable for online shopping whereas search goods are actively traded via e-channels (Kollmann, Kuckertz, and Kayser, 2012; Wells, Valacich, and Hess, 2011; Gupta, Su, and Walter, 2004; Burroughs, and Sabherwal, 2001). Since we are concerned with the reasons why some products are not actively traded over the e-channels, this paper uses experience goods as the focal products to study. The information needed to evaluate search goods is simple and so, the quality of information does not usually matter for search goods. However, when experience goods are concerned, consumers need detailed information for evaluation before making a purchasing decision, and so the quality of information would matter. Therefore, if high-quality information online can compensate for the lack of a physical examination, consumers are expected to actively trade experience goods online just as they do search goods. To achieve high-quality information to substitute physical examinations, sellers have to communicate the information fluently to buyers. The impact of communicated online information might differ across gender and across the various products traded online. Media richness theory explains how consumers require and absorb product information to evaluate products before purchasing them online.

RESEARCH MODEL

Acknowledging that the four communicative aspects of information affect online consumers’ perception of the quality of product information in Lim et al.’s model (2012), we note on the possibility that their four determinants’ effects on information quality (IQ hereunder) may vary across different product groups and gender. Lim et al.’s model pooled different products together to prove their model. Consumers may feel that some products have more experience attributes than others, as Klein (1998) explains. Therefore, it may be useful to separate different product groups from the pool of products in Lim et al.’s model, and test the moderation effect of product types.

Depending on product types, the strength of experience attributes may differ. The levels of telepresence (TL hereunder) and screening capability (SC hereunder) help online consumers experience and identify a product that fits the customer requirement and preference. If a product has stronger experience attributes than other types of products, online consumers may require higher levels of TL and SC to substitute a direct experience, which will result in the perception of higher information quality. In contrast, cognitive overhead (CO hereunder) and channel trustworthiness (CT hereunder) are the contextual information on the websites rather than information about the product itself. Therefore, the seriousness of experience attributes of a product will not have much bearing on the causal relationship between IQ and CO, or between IQ and CT. We believe there will be no moderation effect of CO and CT. Figure 2 is our research model that tests the influence of product types and gender on the causal relationships between information quality and its four determinants of information quality (telepresence, screening capability, cognitive overhead, channel trustworthiness).

H1: Product type has a significant moderation effect on the causal relationship between information quality and telepresence.

H2: Product type has a significant moderation effect on the causal relationship between information quality and screening capability.

H3: There is no moderation effect of product types on the causal relationship between information quality and cognitive overhead.

H4: There is no moderation effect of product types on the causal relationship between information quality and channel trustworthiness.
For demographic factors such as gender effect, there are mixed findings in the e-commerce literature. Donthu and Garcia (1999) and Li et al. (1999) posited a significant influence of demographics including gender on online shopping behaviors, but Gupta et al. (2004) demonstrated that demographics are not an effective basis for the choice between online and offline shopping channels. We believe there will be no gender effect in our model.

If female consumers feel a stronger or weaker level of experience attributes for a product than male consumers, there will be a moderation effect of gender. However, there has been little justifi cation to back that thought in the literature. The strength of experience attributes that online consumers perceive may depend on the individual. Differing gender types may feel a certain level of uncertainty about products that they buy online anyways. Therefore, we hypothesize that there is no moderation effect of gender on the causal relationships between perceived information quality and its four determinants.

H5: There is no moderation effect of gender on the causal relationship between information quality and telepresence.
H6: There is no moderation effect of gender on the causal relationship between information quality and screening capability.
H7: There is no moderation effect of gender on the causal relationship between information quality and cognitive overhead.
H8: There is no moderation effect of gender on the causal relationship between information quality and channel trustworthiness.

**RESEARCH METHOD AND DATA ANALYSIS**

Using the survey instrument presented in Lim et al.'s (2012), we collected and analyzed 309 data from college students in the southeastern area of the U.S. All survey participants have utilized the Internet either as an information source or as a purchasing channel. Sixty percent of survey participants were male, and the remaining 40 percent were female. Eight different products (four product types) on eight different websites were given to the eight different groups of participants respectively. Based on the typical target power level of 0.8, effect size of 0.25 and significance level of 5%, we came up with the appropriate sample size of 53 through G*Power software (Faul et al., 2007). Our sample size for each group of the four product types surpasses the required sample size of 53, as seen in table 2.
To test if any part of Lim et al.’s (2012) research model is affected by the product-specific effect, all path coefficients in the model were tested with equality constraints using EQS 6.1.

Lagrange Multiplier Test (LM Test) in EQS is commonly used to identify significant differences in causal relationships among groups (Byrne, 2006; Kline, 2005). The model with equality constraints for all path coefficients among Group 1, 2, 3, and 4 presented a good fit (see Table 3). LM test did not identify any potential inequality in all causal relationships in the model and there is no significant chi-square difference between with and without equality constraints ($\chi^2_{\text{diff}} = 12.14$, d.f.$_{\text{diff}} = 12$, $\alpha >0.10$) as seen in Table 3. This test attested to the little influence of product type on the model and the consistency of the model across different groups of products. Therefore, hypotheses 3 and 4 are supported while hypotheses 1 and 2 are not supported.

Another test was done on the gender effect. To investigate the gender effect, we divided the data into male and female groups, and ran a LM test with equality constraints on all causal relationships in the structural equation model. The LM test did not signify any potential inequality in the structural model. For both gender groups, all causal relationships were significant, and there is no significant difference between males and females. It is noted that the influence of cognitive overhead on information quality is bigger for female consumers than for male consumers (Female: standardized coefficient $=-3.025$, $p < 0.01$; Male: standardized coefficient $=-1.964$, $p < 0.05$). This basically means that there is no significant difference between the constrained and non-constrained ($\chi^2_{\text{diff}} = 7.47$, d.f.$_{\text{diff}} = 5$, $\alpha >0.10$) as seen in Table 4, which means that there is no significant gender effect on online consumer behaviors. Therefore, hypotheses 5, 6, 7, and 8 are all supported.

### Table 2. Description of Each Product Group

<table>
<thead>
<tr>
<th></th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product type</td>
<td>Digital camera</td>
<td>Apparel</td>
<td>Movie DVD</td>
<td>LCD monitor</td>
</tr>
<tr>
<td>Brand</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>$n$</td>
<td>60</td>
<td>30</td>
<td>34</td>
<td>32</td>
</tr>
<tr>
<td>Total sample size</td>
<td>90</td>
<td>66</td>
<td>64</td>
<td>89</td>
</tr>
</tbody>
</table>

### Table 3. Fit Indices for the Differing Product Types

<table>
<thead>
<tr>
<th>Index</th>
<th>Structural model with equality constraints</th>
<th>Structural model with no constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square (df)</td>
<td>678.34 (444)</td>
<td>690.48 (432)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.915</td>
<td>0.932</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.042</td>
<td>0.039</td>
</tr>
<tr>
<td>90% confidence interval of RMSEA</td>
<td>(0.035, 0.047)</td>
<td>(0.033, 0.044)</td>
</tr>
</tbody>
</table>

### Table 4. Fit Indices for the Gender difference

<table>
<thead>
<tr>
<th>Index</th>
<th>Structural model with equality constraints</th>
<th>Structural model with no constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square (df)</td>
<td>362.81 (221)</td>
<td>355.34 (216)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.926</td>
<td>0.927</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.050</td>
<td>0.051</td>
</tr>
<tr>
<td>90% confidence interval of RMSEA</td>
<td>(0.041, 0.059)</td>
<td>(0.041, 0.060)</td>
</tr>
</tbody>
</table>
DISCUSSION AND CONCLUSION

Among the eight hypotheses in our moderation model, the two unsupported hypotheses of H1 and H2 tested the moderation effects of product types between IQ and TL, and between IQ and SC. The result indicates that online consumers do not differentiate product information from contextual information on the website even though telepresence and screening capability are directly relevant to product information. Another possible explanation for this result might be that the selected eight different products are all experience goods. This means that the level of experience attributes for those products are about the same and likely to create similar differences in their effect on the causal relationships. This issue may be addressed in future studies with additional survey questions about the perceived level of experience attributes of each product.

This study attempted to find out whether different product types or gender matters when information of high quality addresses online consumers’ anxiety toward performance risk. The result of the data analysis shows that there is no effect of gender and product types on the causal relationships. It also indicates that online consumers do not separate the quality of product information from the quality of contextual information, e.g., website quality. Therefore, it is recommended that online vendors pay just as much attention to the contextual information as they do to the quality of product information. This paper contributes to the literature as it completes nomological network of information quality by testing two potential moderators, gender and product type. In the future, gender effects can be further investigated in the actual purchasing stage to see if there’s a difference between perception of information quality and actual purchasing behaviors.

REFERENCES


* More references will be provided upon request to jlim@scsu.edu.