Understanding Online Impulsive Purchase Intention: The Role of Extrinsic Product Cues

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Abstract

How do consumers assess product quality when confronted with multiple cues? This study examines the dissimilar use of product information cues in product evaluations of Web sites. The cue diagnosticity framework is then used to assess the effects of antecedents - engagement, risk, and positive and negative emotions - on consumer cognitive processing and online impulsive purchase. Therefore, four experiments were designed to test the effects of extrinsic cues—ranking and sales—on consumers’ purchase intention. Data collected from 160 customers provide strong support for the research model. The implications of the findings are discussed along with directions for future research.

Keywords

Cognitive processing, engagement, risk, positive and negative emotions, impulsive purchase.

Introduction

With the prevalence of E-commerce, online shopping, via computers and smart devices (mobile phones, tablets, etc.), has become an indispensable part of most people’s daily lives. According to market research by Forrester (2016), the turnover of online retailing in 2016 has amounted to 371 billion new Taiwan dollars (NTD), an eleven percent increase from 2015 (334 billion). This can be attributed to the prevalence of mobile devices, the multi-functionality of Application (APP) services, and the high availability of the network infrastructure design (Rueter, 2016).

One of the disadvantages of online shopping is that consumers cannot directly touch or observe the products to learn about their function and content. Therefore, it is important that online sites present products in a way that embodies all kinds of cues in order to facilitate consumers’ decision-making (Cox, 1967). For example, consumers are able to locate their desired products within a short period of time if the shopping platform has the function to quickly filter information, compare products and prices, and display the products in detail (Chen and Dubinsky, 2003). Easterbrook (1959) puts forward cue utilization theory to further illustrate the tendency for people to collect relevant information based on related environmental cues when performing a task. Utilizing cue utilization theory, this study analyzes the influences of cues that related to online product information on consumers’ purchasing decisions.

According to the cognitive development theory by Piaget (1980), interactions with the environment will affect an individual’s information-processing strategies and representations. Dagher (2007) applies this theory to illustrate the impact of different shopping atmospheres and product information presentation on consumers’ decision-making and behavior. Thus, how to make a deep impression on consumers,
leading them to purchase and repurchase become an important topic in customer behavior research. However, few literatures have conducted an analysis of the time customers spend on cognitive processing, due to the lack of measuring instruments that can accurately record consumers’ attention when making purchase decisions, including view blocks and processing time. However, cognitive processing serves as important bases for understanding consumers’ attention under visual stimulation when browsing for online information. This study uses instrument technology to analyze the impact of different ways of presenting product information on customer processing time and to assess the attractiveness of various cues.

Behavior intention refers to an individual’s response to stimulation from their external environment. From the perspective of the consumer market, it can be interpreted as the behavioral tendency of the customer prior to purchasing a product (Dimoka, 2010; Blackwell, Miniard, and Engel, 2001).

Previous online consumer behavior research (Peter, Olson and Grunert, 1999; Foxall, 2003) has mainly focused on the impact of visible antecedents of commodity cues, generally overlooking antecedents (Baxter Magolda, 1992), which are spontaneous, unconscious, and difficult for others to observe or individuals to express.

**Theoretical Background and Hypotheses**

**Impulse Purchase**

Impulse purchase is defined as an “unplanned purchase,” where a customer makes a purchase decision that was not planned before they entered the store (Stern, 1962). Wood (1998) summarizes the characteristics of consumer impulse buying behavior as follows: lack of planning before purchase, quick decision based on emotion or past experience. Wood emphasizes that impulse purchase is a free, intentional behavior. In short, consumers are free to make purchasing decisions according to their self-awareness and are not forced into these decisions. Stern (1962) indicates that impulse buying can be affected by many antecedents, including economic factors, consumer personality, time, location, and the culture of different regions where products are found. Accordingly, contemporary media provides a variety of extrinsic product cues (e.g., price, brand name) and these are one of the influencing factors of consumer impulse buying (Daft and Lengel, 1984). Based on the above, this study discusses the influence of external stimuli of various products’ extrinsic product cues on the impulse buying of customers.

**Cognitive Processing**

Based on the cognitive development theory by Bruner (1960), the process of transforming things or events in one’s surroundings into personal psychological events is called cognitive representation or knowledge representation. In short, cognition is the acquisition and use of knowledge, involving two levels: the mental structure—that is, how knowledge is stored in our memory and what memory content is stored—and the mental process—that is, the use and processing of knowledge. Research by Holsanova, Holmberg, and Holmqvist (2009) using eye movement has verified that time of attention impacts customers’ purchase intention. Schonke, Renkl, Krieg, Wittwer, Alev, and Salden (2009) further prove that effect of time length of information processing on consumer decision-making. The shorter the time will be spent on processing and the more likely the consumer will be to engage in impulse buying. In conclusion, the following hypothesis is proposed:

**H1:** The consumer’s cognitive processing is negatively correlated with impulse buying.

**Engagement**

Engagement is part of the flow experience, which is the psychological pleasure and recognition that people experience when performing tasks (Websterm and Ahuja, 2006). Engagement emerges at a subconscious level during the external cognitive process (Cook and Campbell, 1979). Research by Gulas and Bloch (1995) has shown that customers are attentive and dedicated to a particular product during the purchasing process, which in turn improves the accuracy of their purchase decisions. Berka (2007) stated engagement in the webpage. In light of this, this study explores engagement as one antecedent to customers' cognitive thinking and decision-making.
Anderson (1990) stated that cognitive processing involves the perception of outward stimuli by an individual as well as the feedback of the individual. Appleton et al. (2006) further argue that when an individual is concentrating on a particular subject, he or she will develop a positive perception of that subject, thereby increasing their favorability and enjoyment at the psychological level. Conversely, if the individual’s engagement is low, the individual tends to develop a negative perception, resulting in less favorability and enjoyment. Therefore, the following hypothesis is proposed:

**H2:** Consumer’s engagement has a positive impact on cognitive processing.

**Risk**

The concept of risk was first proposed by Haynes (1895) to signify the possibility of loss or failure. According to Williams and Heins (1985), the greater the gap between prediction and actual outcome, the greater the risk. Thus, when consumers believe that buying behavior may fail to meet their expectations, they will have a perception of risk (Cox, 1967). Liang and Hu (2015) use neuroscience to verify that consumers’ averaged electroencephalic responses can be used to determine risk factors when they are browsing online products. According to their study, the social cues of online buying environments, such as product ratings, affect consumers’ risk assessment before making a purchase decision. For this reason, this study assesses risk as one of antecedents to customers’ cognitive thinking and decision-making.

Simon et al. (2000) also consider risk an antecedent to cognitive processing. When the perceived risk is higher, personal judgment will be more negative and vice versa. Therefore, the following hypothesis is proposed in this study:

**H3:** Perceived risk by the consumer has a negative impact on cognitive processing.

**Emotions**

Emotion is defined as an individual’s response of emotion to external stimuli (Gaulin, Steven and Donald, 1981). Emotion can be generated by interactions and discourses with others (George, 1996; Gooty, Conelly, Griffith, and Gupta, 2010). Eroglu et al. (2001) state that human emotions can be classified into negative emotions (e.g., anger, sadness, pain) and positive emotions (e.g., joy, excitement, pride). Research by Michel et al. (1989) shows that emotions generated under stimuli in different situations affect cognitive processing because the different types of emotions produced may lead to positive or negative perception on the part of the consumer. Menon and Dubé further state that the more positive the emotional response, the higher the favorability and trust, which promotes smooth development of cognitive thinking; on the other hand, the more negative the emotional response, the higher the sense of distrust and irritation, which in turn interferes with cognitive thinking.

Positive emotion helps people release their tension and produces beneficial effects (Katz, Bernard and Miledi, 1973). Folkman and Moskowitz (2000) further prove that customers are more relaxed when they feel positive about a product, which in turn drives the customer to pay more attention to product information and relatively improves the accuracy of their purchase decision. Seligman (2002) also stresses that positive emotions can widen people’s perspective and make them aware of more environmental details. Hence, this study proposes the positive impact of positive emotion on consumer cognitive processing.

**H4:** The positive emotion of the consumer has a positive effect on cognitive processing.

Negative emotion also affects the customer’s cognitive processing of product information, resulting in less accuracy and efficacy of purchase decisions (Rosenblatt and Ruvio, 1996). Kuhert and Palmer (1991) point out consumers are more likely to have a sense of irritation and insecurity as long as they feel a website is disorganized or hard to use. In addition, negative emotions might emerge during the absorption of product information, leading to negative perception of the product itself and resulting in buying behavior contrary to the seller’s expectations. This is because one negative thought gives rise to more negative thoughts and affects subsequent actions, resulting in more unpleasant emotions, stress, and negative cognitive processing. Therefore, this study also probes into the impact of negative emotion on the consumer’s decision-making process.
H5: The negative emotion of consumers has a negative impact on cognitive processing.

Research Methodology

Research Model

The purpose of this study is to explore the impact of product information on the antecedents to customer information processing in different online shopping situations. Cunningham (2010) divides the antecedents of cognitive processing into two variables. The former includes engagement and risk and the latter includes positive and negative emotions. This study seeks to understand the impact of customers’ cognitive processing of information on impulse buying by utilizing the following research model:

Framework of Online Extrinsic Cue Design

The cues embodied in the product itself can be divided into intrinsic and extrinsic cues (Olson, 1972). Intrinsic cues include the properties of the product itself, such as color and shape; extrinsic cues are attributes added by people, such as price and evaluation. As it is impossible for consumers to directly observe the cues of packaged products, they tend to evaluate values (Wells et al., 2011). For this reason, extrinsic cues are the key element in a consumer’s decision-making process. Suki (2013) argues that with the prevalence of e-commerce, online shopping has replaced traditional in-store purchasing. However, consumers have doubts about the products themselves, as it is hard for them to touch or otherwise check the quality of online products. Therefore, when consumers are faced with uncertainty, it is more difficult for them to make accurate judgments about products.

Generally, consumers to make decisions based on three to five product attributes rather than all available information (Olson, 1972; Brady and Bourdeau, 2005). Therefore, this study chose three extrinsic product cues to explore customers’ cognitive decision-making. We regarded ranking and sales as two extrinsic product cues based on the study by Wang et al., (2016) and divided them into High Ranking (HR)/Low Ranking (LR) and High Sales (HS)/Low Sales (LS). Based on these cues above, we further divided shopping websites into four categories: High Ranking/High Sales, High Ranking/Low Sales, Low Ranking/High Sales, and Low Ranking/Low Sales. The four categories were designed to explore the impact of antecedents on consumer cognitive processing under the stimulation of different extrinsic product cues as well as their impact on purchase desire and impulse buying.

According to previous studies on online shopping, the two extrinsic cues of product ranking and sales play an important role (Kumar, 2006; Chen, 2008). As product ranking and sales are based on post-purchasing statistical data, compared with sales, product rating provides a more prediction of the performance of a product and is viewed as highly diagnostic in risk and engagement (Novemsky and Kahneman, 2005; Kahneman et al., 1991). Therefore, this study classified product ranking and sales into High Ranking (HR)/Low Ranking (LR) and High Sales (HS)/Low Sales (LS) to explore the subjects’ decision-making processes in different situations. The study defined rankings from 4.75 stars to 5 stars as High Ranking (HR) and 2 stars to 2.25 stars as Low Ranking (LR). With respect to sales, the study sorted the sales of a total of 5000 products and defined the top 100 sales as High Sales (HS) and the bottom 100 sales as Low Sales (LS).

Survey Administration

The research model was tested using data obtained from online shoppers in Taiwan. The first page of the questionnaire explains the purpose of this study and assures confidentiality. A total of 160 valid samples were used after subtracting incomplete questionnaires. The study offered the subjects a monetary bonus (US$ 5 each) after confirming that the data were complete and the questionnaires were valid. Table 1 lists the demographic information of the respondents.
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Twenty-third Americas Conference on Information Systems, Boston, 2017

Table 1. Demographic profile of respondents.

<table>
<thead>
<tr>
<th>Variable</th>
<th>HR-HS (N=39)</th>
<th>HR-LS (N=39)</th>
<th>LR-HS (N=38)</th>
<th>LR-LS (N=44)</th>
<th>Total (N=160)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>27</td>
<td>31</td>
<td>30</td>
<td>31</td>
<td>119</td>
<td>74.38%</td>
</tr>
<tr>
<td>Female</td>
<td>12</td>
<td>8</td>
<td>8</td>
<td>13</td>
<td>41</td>
<td>25.62%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>21</td>
<td>10</td>
<td>12</td>
<td>10</td>
<td>13</td>
<td>45</td>
<td>28.12%</td>
</tr>
<tr>
<td>22</td>
<td>7</td>
<td>0</td>
<td>7</td>
<td>2</td>
<td>16</td>
<td>10.00%</td>
</tr>
<tr>
<td>23</td>
<td>12</td>
<td>27</td>
<td>21</td>
<td>26</td>
<td>86</td>
<td>53.75%</td>
</tr>
<tr>
<td>24</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>6.25%</td>
</tr>
<tr>
<td>More than 25</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>1.88%</td>
</tr>
<tr>
<td>Hours of use of the Internet</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3-5 hours</td>
<td>1</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>15</td>
<td>9.37%</td>
</tr>
<tr>
<td>5-7 hours</td>
<td>28</td>
<td>0</td>
<td>1</td>
<td>26</td>
<td>55</td>
<td>34.37%</td>
</tr>
<tr>
<td>7-9 hours</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>7</td>
<td>47</td>
<td>29.37%</td>
</tr>
<tr>
<td>More than 9 hours</td>
<td>0</td>
<td>24</td>
<td>12</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience of using online shopping</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-2 years</td>
<td>1</td>
<td>0</td>
<td>8</td>
<td>3</td>
<td>12</td>
<td>7.50%</td>
</tr>
<tr>
<td>2-3 years</td>
<td>8</td>
<td>13</td>
<td>13</td>
<td>4</td>
<td>38</td>
<td>23.75%</td>
</tr>
<tr>
<td>4-5 years</td>
<td>5</td>
<td>3</td>
<td>9</td>
<td>4</td>
<td>21</td>
<td>13.13%</td>
</tr>
<tr>
<td>5-6 years</td>
<td>8</td>
<td>11</td>
<td>6</td>
<td>19</td>
<td>44</td>
<td>27.50%</td>
</tr>
<tr>
<td>More than 6 years</td>
<td>17</td>
<td>12</td>
<td>2</td>
<td>14</td>
<td>45</td>
<td>28.12%</td>
</tr>
<tr>
<td>Frequency of online purchases (years)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Once every three days</td>
<td>1</td>
<td>24</td>
<td>11</td>
<td>7</td>
<td>43</td>
<td>26.88%</td>
</tr>
<tr>
<td>Once a week</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>2</td>
<td>18</td>
<td>11.25%</td>
</tr>
<tr>
<td>Once a month</td>
<td>8</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>15</td>
<td>9.38%</td>
</tr>
<tr>
<td>Once every three months</td>
<td>21</td>
<td>5</td>
<td>12</td>
<td>27</td>
<td>65</td>
<td>40.62%</td>
</tr>
<tr>
<td>Twice a year</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>13</td>
<td>8.12%</td>
</tr>
<tr>
<td>Once a year</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>3.75%</td>
</tr>
<tr>
<td>no experience</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>Frequency of drinking coffee (years)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Once a day</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0.63%</td>
</tr>
<tr>
<td>Once a week</td>
<td>4</td>
<td>20</td>
<td>16</td>
<td>12</td>
<td>52</td>
<td>32.50%</td>
</tr>
<tr>
<td>Once a month</td>
<td>5</td>
<td>11</td>
<td>10</td>
<td>9</td>
<td>35</td>
<td>21.88%</td>
</tr>
<tr>
<td>Once every three months</td>
<td>2</td>
<td>8</td>
<td>6</td>
<td>5</td>
<td>21</td>
<td>13.12%</td>
</tr>
<tr>
<td>Twice a year</td>
<td>23</td>
<td>0</td>
<td>2</td>
<td>14</td>
<td>39</td>
<td>24.37%</td>
</tr>
<tr>
<td>Once a year</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0.62%</td>
</tr>
<tr>
<td>no experience</td>
<td>5</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>11</td>
<td>6.88%</td>
</tr>
</tbody>
</table>

Note: HR=High Ranking, LR=Low Ranking, HS=High Sales, LS=Low Sales

Data Analysis

A two-step approach, recommended by Anderson and Gerbing (1988), was adopted for the data analysis. The first step involves the analysis of the measurement model and the second step tests the structural relationships among the latent constructs. The aim of the two-step approach is to establish the reliability and validity of the measures before assessing the structural relationship of the model. SmartPLS 3.0 was used because it allows latent constructs to be modeled as formative or reflective indicators. PLS places minimal restrictions on the measurement scales, sample size, and residual distribution (Chin and Newsted, 1999).
Measurement Model

The adequacy of the measurement model was evaluated based on the criteria of reliability, convergent validity, and discriminant validity. Reliability was assessed based on the composite reliability values. Our measurements show that: (1) all indicator loadings should be significant and exceed 0.7 and (2) the Average Variance Extracted (AVE) for each construct should exceed the variance according to the measurement error for that construct (i.e., the AVE should exceed 0.50). The whole analysis shows that all of the items exhibit a loading higher than 0.7 on their respective constructs.

Discriminant validity was examined by using the following three tests. First, the cross factor loadings indicate that there exists good discriminant validity because the loading of each measurement item on its assigned latent variable is larger than its loading on any other construct (Chin, 1998). Second, the correlations among the constructs are all well below the 0.85 threshold (Kline, 1998), suggesting the existence of discriminant validity. Third, the square root of the AVE from the construct is much larger than the correlation between the construct and other constructs in the model. This also demonstrates the existence of discriminant validity (Fornell and Larcker, 1981).

Structural Model

This study further tested the structural paths of the models among four groups: High Ranking/High Sales, High Ranking/Low Sales, Low Ranking/High Sales, and Low Ranking/Low Sales. We classified them into group A, group B, group C, and group D. The following provides the magnitude and significance of inter-construct relationships. The results are summarized below.

In the group A (High Ranking/High Sales), there are two independent variables that can positively affect cognitive processing: Risk ($\beta=0.463$, $p<0.01$) and Positive Emotion ($\beta=0.339$, $p<0.01$); cognitive processing has a positive effect on impulse purchase ($\beta=0.586$, $p<0.01$).

In the group B (High Ranking/Low Sales), there are three independent variables that can positively affect cognitive processing: Engagement ($\beta=0.273$, $p<0.05$), Risk ($\beta=0.354$, $p<0.01$) and Negative Emotion ($\beta=0.422$, $p<0.001$); cognitive processing has a positive effect on impulse purchase ($\beta=0.66$, $p<0.001$).

In the group C (Low Ranking/High Sales), there are three independent variables that can positively affect cognitive processing: Engagement ($\beta=0.504$, $p<0.05$), Risk ($\beta=0.626$, $p<0.05$), and Negative Emotion ($\beta=0.667$, $p<0.001$); cognitive processing has a positive effect on impulse purchase ($\beta=0.663$, $p<0.001$).

In the group D (Low Ranking/Low Sales), there is only one independent variable that can positively affect cognitive processing: Negative Emotion ($\beta=0.706$, $p<0.001$); cognitive processing has a positive effect on impulse purchase ($\beta=0.641$, $p<0.001$).

Hypothesis 1, Supported: The path from cognitive processing to impulse purchase is positive and significant.

Hypothesis 2, partially supported: Except the group A (High Ranking/High Sales) and the group D (Low Ranking/High Sales). The path from Engagement to cognitive processing is positive and significant.

Hypothesis 3, Supported: The path from Risk to cognitive processing is not positive and significant.

Hypothesis 4, partially Supported: Except the group B (High Ranking/Low Sales) and the group C (Low Ranking/High Sales) and the group D (Low Ranking/High Sales) The path from Positive Emotion to cognitive processing is not positive and significant.

Hypothesis 5, partially Supported: Except the group A (High Ranking/High Sales). The path from Negative Emotion to cognitive processing is positive and significant.

In sum, the research model accounted for 61.5% to 79.2% of the explained variance in impulse purchase. Therefore, the fits of the four conditions models are acceptable. The results indicate that different cues in online shopping can have different effects on consumers’ buying decisions.
Conclusion

This paper reports the preliminary findings of the experiment design using four different kinds of shopping websites and two extrinsic cues—ranking and sales—to explore the effects of cognitive processing on consumer impulsive purchase intention. The valid data collected from 160 customers provide strong support for the research model. A fair comparison of four research models was presented, and the key conclusions were:

First, consumers are simultaneously exposed to multiple extrinsic cues, and they usually process each product cue in relation to the others. We designed the measurement of two different cues (sales and ranking) with high- or low-scope in order to test the positive or negative inferences evoked by the high- or low-scope cues. The results provide support for cue diagnosticity theory. Second, past research has typically only used one antecedent to design measurement. This study uses several, combining questionnaire data to explore the four antecedents of cognitive processing and their effects on online impulse purchase intention. This provides a more holistic explanation of consumers’ cognitive processing than using only one antecedent alone.

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