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CROSS-WEBSITE NAVIGATION BEHAVIOR AND PURCHASE COMMITMENT: A PLURALISTIC FIELD RESEARCH

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Abstract

The increase in the variety of websites, ranging from information-intensive portal, through social media, to shopping website, has afforded consumers unprecedented opportunity to make informed purchase decisions. Anecdotal evidence indicates that consumers do spend considerable amount of effort visiting various online outlets, such as the social media websites, prior to committing to a purchase. This could suggest that online consumers in general are conscious-buyers who have a tendency to engage in reasonably wide amount of product research beyond the shopping websites. Building on the selective exposure theory, this research argues that online consumers are selective and focus in their product research endeavor; specifically, these consumers may have a tendency to biased process the exposed informational alternatives to gratify their needs for purchase through shopping websites. To validate this proposition, we collaborated with a Chinese Internet-based research agency to perform a pluralistic investigation, which involves a non-obtrusive tracking of 200 Chinese consumers' online activity and a series of post-investigation interviews.

In terms of tracking of the consumers' activities, our novel analyzing technique, sequence analysis, can be used to categorize the distinctive clusters of cross-website navigations. In each distinctive cluster, consumers engaging in product information retrieving activities are more likely to commit to a purchase within a visit even after taking into consideration the previous visits' activities. Based on previous work, we argue that visits to different types of information media influence the online purchase commitment variously. The subsequent interview designs with a subset of consumers will be conducted to reveal that consumers have an inclination to gratify the reasons for purchase by focusing on visiting shopping websites; while other websites serve as good avenues to gratify reasons for non-purchase in the future.

Keywords: *Internet navigation behavior, selective exposure theory, online purchase*

1 INTRODUCTION

Traditional consumer researchers argued that consumers embark upon information seeking activities before making purchase decision in the offline settings (Blackwell et al., 2006; Engel et al., 1968). However, with the access to extensive variety of websites, the informed purchase decision has never been thus unprecedentedly vacillating. And the information seeking stage ahead of purchase decision is exponentially elaborated in the online settings, which has aroused widespread attention. For instances, the traditional product classification models by information searching endeavor could be challenged due to the comparatively lower information searching cost at internet (Nelson 1970, 1974; Alba et al. 1997; Klein 1998; Lynch & Ariely 2000); the online consumers was also classified and addressed in terms of observing the whole online information deliberating process within a single commercial website (Moe 2003).

Anecdotal evidence indicates that consumers do spend considerable amount of effort visiting various online outlets, such as information-intensive portals, search engines, social media, or commercial websites, prior to committing to a purchase. For instance, Johnson and his colleagues (2004) revealed that active online consumers have a tendency to search information across multiple websites in their purchase decision making, even for commodity-like products such as books and CDs; Danaher and his associates (2006) observed that the amount of time spent on entertainment websites is much more than that of portal websites, and the extent of advertising on a website influences consumers' visit duration; another study argued that consumers usually engage in significant information seeking behavior via search engines or information portals when making purchase decisions (Gremett 2006); some works also pointed out that social media websites populated by user-generated content (e.g., word-of-mouth) might exert a non-trivial influence on purchase conversions (Brown et al. 2007; Limayem et al. 2000). All these works could suggest that online consumers in general are conscious-buyers who have a tendency to engage in reasonably wide amount of product research beyond the shopping websites.

The availability of clickstream data i.e., records of a series of web pages visited by a user while engaging in web navigation and visiting activities, has engendered the possibility for scholars to analyze actual consumers' pre-purchase information seeking activities. For instance, some scholars have leveraged on clickstream data from a specific shopping website to study how a consumer seeks product-related information within that particular website (Johnson et al. 2004). Other studies have utilized the clickstream data to predict surfer-to-buyer purchase conversion (e.g., Moe & Fader, 2004; Moe 2003; Montgomery et al. 2004). However, little attention has been paid to investigate the whole visiting process across multiple online outlets. And this is a particularly pertinent concern given that consumers typically do not visit a single website to accomplish a shopping task (Park & Fader 2004). Thus motivated, the current research is proposed to address this concern and attempts to answer the question raised above by identifying the consumers' pre-purchase information seeking patterns cross-website navigations, and ascertain the characteristics of those that eventually lead to purchase commitments.

Building on the selective exposure theory, the objective of current research proposal is to argue that online consumers are selective and focus in their product research endeavor; specifically, these consumers have a tendency to biased process the exposed informational alternatives to gratify their needs for purchase through shopping websites. Before investigating this research question, it is necessary to employ an appropriate analysis technique on consumers' clickstream data to identify the information seeking patterns that span multiple websites. Thus, we propose the sequence analysis technique to organize the website visits recorded in the clickstream data into sequences, and the backbone of this article is to introduce how to implement the sequence analysis in the online consumer behavior research. It's notable that the data was collected from the real work in terms of collaborating with an IT consulting company headquartered in China. Unceasingly, in order to purify the quantitative results, the in-depth interviews will be conducted from the real world in the future

research. Especially, we are eager to understand the deep-seated reasons wielded to remark the manifestations shown from the quantitative results. Ulteriorly, the investigation should be located on the linkage between consumers' perceptions of choosing specific information source for product research endeavor with the identified navigational patterns reinforcing the purchase commitment propensity.

The remainder of this paper is organized as follows. In the next Section, we introduce the theoretical framework, the selective exposure theory. In Section 3, we present a sufficient review of the prior literature and hypotheses development derived from above theoretical framework, and highlight how our study bridges the existing gaps. The subsequent Section outlines research designs, one quantitative study design and one qualitative study design for future research. Specifically, the detailed analyzing technique will also be included in the quantitative design. We conclude the article by discussing the potential theoretical and practical implications as well as the remaining future work in the last Section.

2 SELECTIVE EXPOSURE THEORY

The selective exposure theory is originally derived from the cognitive dissonance theory, and it refers to that the individuals selectively expose themselves to external stimuli (Festinger 1957). From the information processing perspective, the selective exposure theory advocates that the individuals prefer to seek information consistent with their pre-existing opinions while avoiding the information that contradict their pre-views (Frey 1986; Frey & Wicklund 1978; D'Alessio & Allen 2007). The approach of this theory relies on assumption that the individuals conduct the information-seeking behaviors continuously with oriented goals (Frey 1986). Notably, this goal-oriented assumption also fits consumer decision process. In the consumer purchase process, we can find that the consumers also spontaneously search for diverse information after recognizing their need. Thus, the visible linkage between the selective exposure theory and consumer purchase process is standing to reason. Namely, ahead of product-related information seeking activities, the consumers have formalized the goals or objects (clear or blur) to look for.

Most of the previous literatures discussing selective exposure theory are restricted in psychology and communication fields. For instances, the rudiments of selective exposure theory were originally derived from cognitive dissonance theory by Festinger (1957), who advocated that individuals always actively averted the situation to be exposed with dissonance informational alternatives; Zillmann and Bryant (1985) suggested that people often prefer to sustain the cognitively consonance equilibrium rather than disproportionate this cognitive balance in the communication process; Frey (1986) revised the experimental design and manipulations to provide empirical support to that the selective exposure to information exists. Additionally, selective exposure, as a phenomenon, has also shown its higher adaptability in terms of linking with other psychological theories. For instances, in the choice certainty theory (Mills 1968), it's purposed that decision makers tend to increase and avoid decreasing certainty to reinforce or convince themselves that their choices are better than the other alternatives prior to committing their decisions; in the action phase theory, Gerard (1967) suggested that the decision makers paid selective attention to the information in terms of denigrating the rejected alternatives and bolstering the supportive alternatives ahead of making decision due to the biased information process; the selective information processing activities also shed light upon the conflict theory, and Janis and Mann (1977) described the defensive avoidance in the decision making process where the decision makers bolstered the least objectionable alternatives and increased the attractiveness of chosen alternatives when facing with decision conflict.

Avant this study, our comprehensively extent of literature review suggests the limited prior works deployed selective exposure theory for either marketing or consumer research. And all these relevant works only made mention of the selective exposure phenomena instead of utilizing it as the theoretical framework. For instances, Mittelstaedt (1969) discussed the offline buyers' post-decision behaviors from dissonance approach; another research work utilized a longitudinal study to argue the selective exposure effect in the television advertising strategies (Moschis & Moore 1982); Hulbert and Capon

(1972) conceptualize a paradigm of selective exposure derived from a interpersonal communication process. However, all these works discussed the consumer behaviors in the offline context and are in shortage of the knowledge of the behaviors of online consumers.

In Frey's work (1986), besides the provision of empirical support to selective exposure theory in information processing, he also addressed the implication for future research on selective exposure to information. For instances, Frey also advocated that it is worthwhile to integrate selective exposure theory into other theoretical frameworks; he also suggested the field research outside the laboratory is necessary (we still didn't find any field studies utilizing the selective exposure theory so far); and the sequential information-seeking activity need to be investigated more in-depth for better explaining the selective exposure theory. Moreover, he also suggested the cost and amount of information also play roles in the dissonant information processing in the pre-decision process. In this case, the internet opportunely can provide high amount of information with low cost. Overall, we have sufficient reasons to believe that our work can provide not only strong empirical support to the selective exposure theory but also the theoretical contribution for extending the existing theoretical framework. In the following section, we firstly present a sufficient review concerning allied prior literature. We will then introduce our research model and hypotheses, and explain how this study replenish the deficiency of prior work and gap the bridge between consumer decision process and the selective exposure theory.

3 RESEARCH MODEL AND HYPOTHESES

Recalling the essence of our research question, we want to determine how consumers tend to biased process the exposed informational alternatives which affect their online purchase commitment propensity. To do so, it is necessary for us to identify the navigational patterns in the initial stage. And then, we identify which informational alternatives associated with specific navigational pattern(s) affect(s) purchase propensity. Due to the seldom prior literatures focusing on the whole navigation sessions, we draw some viewpoints from a study summarizing the consumers visiting patterns within a single commercial website (Moe 2003). Controlling the cases of future purchasing decision, there are two types consumers, namely 'Search/Deliberation' and 'Knowledge Building'. And the most significant discrimination of these two groups is the exposed information to the consumers. The 'Search/Deliberation' consumers seek the information based on the initiatively searched results, and the 'Knowledge Building' consumers tend to browse information pages. Before utilizing the conclusion, we need to examine that the consumers are not the immediate buyer but having showed the purchase intention in the previous sessions, which is supported by the analysis results described in the next section. Returning to Moe's conclusion (2003), characteristics of 'Search/Deliberation' consumers' strategies could include intensive search within a product category or attributes. In our context, the consumers may switch staying between commercial websites and search engines for better comparison. In other words, based on the informational needs of these consumers, the search engines are the most suitable medium for gratifying them. Hence, we hypothesize the following.

Hypothesis 1A (H1A): For within visit session, the density of utilizing the search engines enhances the purchasing conversion for the consumers who make the deliberation during visiting an e-commerce website.

Moe has shown that the 'Knowledge Building' consumers spend most of visits on information contents. Analogous, we hypothesize the following.

Hypothesis 1B (H1B): For within visit session, the density of visit to information portals enhances the purchasing conversion for the consumers who complete the deliberation before entering e-commerce website.

Remarkably, although there are various papers demonstrating how the consumers deployed the search engines or searching functions from other sites to conduct the pre-purchase research, most of these papers are consistent with our purposed hypothesis 1A (H1A). For instance, Johnson et al. (2004)

advocated that most of the consumers spent less effort on searching activities for product research prior to purchase in terms of longitudinally observing how the consumers use search engines for three different products. Recalling the definition of the ‘Knowledge Building’ by Moe (2003), one key characteristic of these ‘knowledge builders’ is to make the purchasing decision in the future. In other words, the purchase decision can only be detected across session rather than one single session. Therefore, we didn’t purpose the hypothesis to investigate the relationship between the density of utilizing search engines and the purchasing conversion for the consumers who complete the deliberation before entering e-commerce website.

A recent Mckinsey’s report showed that the term, social search based on social media, started to emerge around 2004 with the boom of various social network platforms (Bughin et al. 2011). As a brand-new information media, impact of social media has also been exemplified in the academia. For instance, one recent work examined that power of electronic WOM (Word-of Mouth) effect by twitter data (Jansen et al. 2009). At all events, the impact of social media on electronic commerce is still under debate. Notwithstanding, some works pointed out that social media websites populated by user-generated content (e.g., word-of-mouth) might exert a non-trivial influence on purchase conversions (Brown et al. 2007; Limayem et al. 2000). However, the user-generated content ineluctable covers different users’ own opinions, which may include the thinking of some affairs, daily sundries or status, and reviews or comments on products, advertisements or marketing campaigns etc. Markedly, the reviews or comments have highly relevance to online purchase decision. Furthermore, both marketing and economic scholars have demonstrated the negative information cues are more powerful influence on individuals than the positive ones, which is called prospect theory in behavioral economics (Chevalier & Mayzlin 2006; Kahneman & Tversky 1979). Moreover, in social media, the individuals need to face the information overload problems, which can also reduce the resulting positive impact on the information. Comparing to the comparatively objective results from search engines or portal sites, the information from social media is glutted with the personal opinions or overloaded information. Either of them has been proved more negativity than positivity. Hence, we have sufficient reasons to believe that the goal-oriented consumers visit social media to seek for the “dissonant voices” to convince themselves to terminate the purchasing intention. Accordingly, we hypothesize the following.

Hypothesis 2 (H2): For within visit session, the density of visiting social media at deliberation process impairs the purchasing conversion.

So far, the hypotheses have been developed, and a visualized research model is displayed at Figure 1.

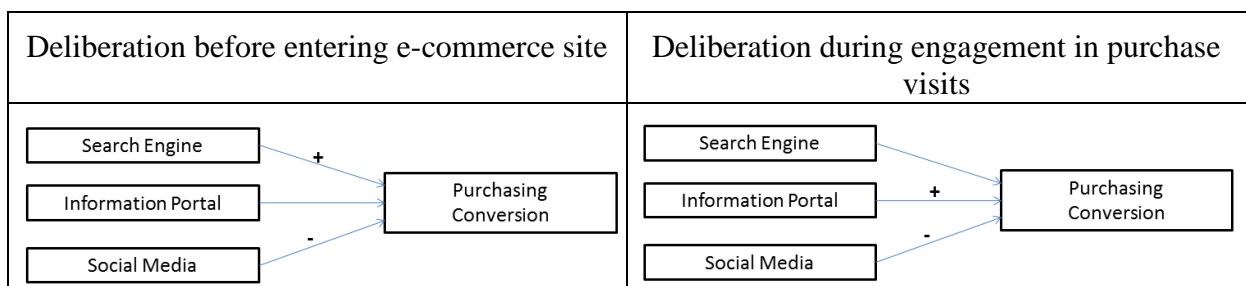


Figure 1

4 RESEARCH DESIGN

In this section, we outline two study designs, a field study and a qualitative design respectively. Both of these two works are research in process. For the first study, we will elaborate the analyzing technique, sequence analysis to demonstrate how this technique can be applied in the research of online consumer behaviors.

4.1 A field experiment

4.1.1 The Analysing Technique: Sequence Analysis

In its simplest terms, sequence analysis refers to a systematic way of organizing actions (or events) according to chronological order (or distribution of), and the exact times during which the actions occurred (Abbott 1995; Durbin 1998). The technique has been applied in several disciplines to study phenomena that involve sequences of actions, occurrences, developments, and progressions. In relation to our e-commerce context, we applied the sequence analysis technique to model and analyze the sequences of consumers navigating from one website to another during their web browsing sessions, and accordingly identified the patterns in these cross-website navigation sequences. In particular, we applied sequence analysis with an optimal matching algorithm to compare the similarities and dissimilarities among the navigation sequences, with the aim of allowing unique patterns to emerge from these sequences. The optimal matching algorithm has been widely shown to be reliable (Durbin 1998; Abbott & Hrycak 1990; Abbott 1995; Sankoff & Kruskal 1983), and is appropriate for this study since it is capable of accommodating complex sequences of different lengths (Sankoff & Kruskal 1983), which are typical of web browsing sessions (Moe 2003).

The central gist of the optimum matching algorithm is to derive numeric representations of a given set of sequences (i.e., $S_1, S_2, S_3, \dots, S_n$) in support of subsequent statistical analysis. A sequence (e.g., S_1) denotes a series of events or website navigation actions made by a consumer, as in our case. The differences among the studied sequences (i.e., $S_1, S_2, S_3, \dots, S_n$) are represented by two matrices, namely the substitution cost matrix and the optimal matching distance matrix (Levenshtein 1966). The two matrices serve as a complete numeric representation of the given entire set of sequences. Specifically, the two matrices can be derived based on studying (with respect to the entire set of sequences) by 1) the difference within a sequence (the focus of the substitution cost matrix) and 2) the difference between two given sequences (the focus of the optimal matching distance matrix). To explain the two matrices, we referred to an exemplary set of 5 sequences in Table 1 for illustration.

| |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| S_1 : A->B->C->B->A |
| S_2 : B->A->C->B->A |
| S_3 : C->A->C->B->A |
| S_4 : C->B->C->B->A |
| S_5 : B->C->B->C->A->C |
| 1) The alphabets, A, B, and C, denote the specific, unique website navigated; and 2) the number of events (i.e., the number of website navigations) could differ from one sequence to another. |

Table 1

The substitution cost matrix contains the cost of substituting an event (or website navigation actions in our case). The substitution cost can be obtained by observing the probability of event j at sequential position $t+1$ given that the event i is observed at sequential position t . Here, we use $P(i/j)$ to indicate the probability of event j at sequential position $t+1$ given the event i and $i \neq j$. Accordingly, the substitution cost can be derived by Formula 1 below.

$$Cost(i,j)=2-Prob(i/j)-Prob(j/i) \quad (1)$$

Referring to Table 1 above, there are 5 sequences (i.e., $S_1 \dots S_5$) with 3 distinct events $\{A, B, C\}$. We can first obtain the $Prob(j/i)$ value, where i or j is part of $\{A, B, C\}$ and $i \neq j$. For instance, the value of $Prob(C/B)$ is $4/21$, where 4 is derived by the number of times of occurrences of “B->C”, and 21 is the total number of successive pair events in the whole set of sequences. Similarly, we can obtain $Prob(B/C)$ i.e., $6/21$. Referring to Formula 1, we can determine that the substitution cost between event ‘B’ and ‘C’, $Cost(B,C)$, is equal to 1.5238, which is derived from: $2-4/21-6/21$. Afterwards, each pair of events can be calculated in the same way, and the values are 1.7143 and 1.8095 for $Cost(A,B)$

and $Cost(A,C)$ respectively. Then, we can arrange the substitution costs into a symmetrical matrix called the substitution cost matrix.

The optimal matching distance matrix consists of the minimum transformation cost for converting one sequence (S_i , where $i \in \{A,B,C,\dots,n\}$) to another sequence (S_j , where $j \in \{A,B,C,\dots,n\}$ and $i \neq j$) through three forms of operations, i.e., insertion, deletion and/or substitution. It is to be noted that the insertion or deletion cost is set to be a fixed value that is slightly higher than the maximum possible substitution cost (Abbott & Hrycak 1990). Here, we set the deletion or insertion cost as 2, because the maximum possible value of substitution cost is less than 2 in our case. The maximum value of $Cost(i,j)$ is 1.946 in the substitution cost matrix after calculation. By using the same example in Table 1, we illustrate how it works: If we want to convert S_1 to S_3 (sequences with same length), we need to replace the events at Positions 1 and 2 from either S_1 or S_3 . Referring to the substitution cost calculated previously, we can obtain the values, $Cost(A,C)$ and $Cost(A,B)$, which is 1.8095 and 1.7143 respectively. Thus, the minimum transformation cost is 3.5238 (1.8095+1.7143). For the sequences with different lengths such as S_4 and S_5 , the transformation process is more complicated. Intuitively, we can replace the event at Positions 1 to 4, and then insert a new event, C, at the end of S_4 or delete the event, C, at the end of S_5 . In that way, the transformation cost is 8.0952 (1.5238+1.5238+1.5238+1.5238+2). However, we can also select an alternative way of transformation. By inserting (deleting) an event, B, in the beginning of S_4 (S_5) and shifting the rest of the sequence to the right (left) side to make these two sequences with the same length, afterwards, we can replace the rest of the different events at a homologous position. The transformation cost is equal to 5.333 (2+1.5238+1.8095), which is much smaller than 8.0952. There are other possible ways of transformation and our approach is to determine the minimum transformation cost. For instance, in relation to the above case, we can insert (delete) an event within S_4 (S_5) and substitute the other heterogeneous events to make two sequences the same, while the transformation cost is always greater than 5.333. Thus we can determine that the minimum transformation cost is 5.333, which is also called the optimal matching distance between these two sequences. Since the optimal matching distance matrix contains the values of the transformation costs of pair-wise sequences, it is symmetrical and its size is determined by the number of sequences in the whole data set.

4.1.2 Data description and Transformation

We collaborated with a leading China-based Internet market research firm to collect the necessary empirical data. We obtained a set of navigational clickstream data entailing 200 Chinese consumers' cross-website navigation activities for 30 consecutive days. The data was collected by installing a tracking-program on consumers' computers through which their Internet usage behavior was tracked with their permission. It must be stressed that the tracking application was installed on the participating consumers' computers much earlier than this research was conducted. Hence, neither the collaborating market research firm nor the participating consumers were aware of the objective of this research. Any URL viewed by the user in his/her browser window was recorded. Incentives were offered to the consumers in return for their permission to track their browsing activities. The Internet browsing records of 100 female and 100 male Internet users in China were randomly selected throughout November 2010. A total of 453,347 unique records were generated by the panelists during the observation period. For each record, several attributes were recorded, including the user id, visit timestamp, visit time length, and domain information. This was in addition to a description of the nature of the websites and web pages.

To gain systematic insights into the navigation behaviors across websites, we encoded the clickstream data into a sequential format comprising sessions. A session entails continuous navigations of pages from when a consumer commences navigation until that consumer decides to terminate the navigation. Following the typical computer system defaults, we assumed that a session ended if a user stopped navigating for 60 minutes based on the simple descriptive results i.e., the user was idle with no navigation activity. This yielded 2,048 sessions as training data for the analytic model. Subsequently, we classified every visit made by the consumers into one of the following seven categories,

Multimedia, Search Engine, Social Media, Information Portal, E-commerce, Company Site, and Navigation Portal. In addition, we used a binary value to indicate whether a purchase commitment was made during a session (1 indicates a purchase was made and 0 indicates no purchase was made). The purchase commitment was identified by examining the URL indicating the payment transaction in our panel data.

4.1.3 Remainder Work for Future Research

Thus far, we have elaborated the detailed procedures, including the technique and clickstream data conversion, for analysing the cross-websites consumer browsing behaviors. For future research, we will continue to be engaged in two perspectives. First, based on the dissimilarity matrix obtained from optimal matching algorithm, we can utilize it as an inputting matrix for cluster analysis to obtain the distinctive navigational patterns. Second, besides investigating in each session, we can also examine whether the consumers have shown purchasing propensity in terms of investigating the visiting to E-commerce sites in previous sessions. Third, for each cluster, we can examine whether the different types of information media, such as information portals, social media, or search engines, affect the purchasing commitment in order to test our hypotheses.

4.2 Study 2 – Peer to Peer Interviews

We distributed the interview recruitment advertisement in collaboration with the consulting company. All of informants will be interviewed individually in one session lasting 20 minutes to 40 minutes in length, following a relatively semi-structured and evolving interview framework (Stewart et al. 2007). The semi-structured questionnaires are initially exploited in English. And then we translated it into Chinese while keeping consistency with terminology usage and sentence structures maximally. A double-blind crossover translation from Chinese back to English was also conducted by a bilingual (native English and Chinese) IS professor, who is not involved in this research project. All interviews were recorded and transcribed and typed. And the interviewees were paid 50 Chinese Yen (8 U.S. Dollars) as incentives. The detailed interview will be conducted in the future.

5 CONCLUSION

In this proposal, we addressed a pluralistic methodology to better understand the consumers' information seeking behaviours prior to purchase in the purchase decision process. To do so, in study 1, we introduced how to codify the data of the web log files into session formats, based on which sequence analysis was applied with optimal matching algorithm to derive four distinctive clusters of web navigation patterns which might otherwise have appeared elusive. In order to triangulate the findings and verify our speculation, the in-depth peer to peer interviews will be conducted in study 2. We hope this proposal work can be better updated based on your comments.

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