MIXING CONSUMERS’ RATIONALITY AND SOCIALITY: EFFECTS OF PRODUCT QUANTITY AND POPULARITY INFORMATION ON ONLINE SHOPPING

Yan Yu  
Renmin University of China, yanyu@ruc.edu.cn

Chuanqi Wang  
Renmin University of China, wangchuanqi_ruc@163.com

Keyi Luo  
Renmin University of China, lky1994417@163.com

Ben Liu  
City University of Hong Kong, ben.liu@cityu.edu.hk

Follow this and additional works at: http://aisel.aisnet.org/pacis2016

Recommended Citation

Yu, Yan; Wang, Chuanqi; Luo, Keyi; and Liu, Ben, 'MIXING CONSUMERS’ RATIONALITY AND SOCIALITY: EFFECTS OF PRODUCT QUANTITY AND POPULARITY INFORMATION ON ONLINE SHOPPING” (2016). PACIS 2016 Proceedings. 120.  
http://aisel.aisnet.org/pacis2016/120

This material is brought to you by the Pacific Asia Conference on Information Systems (PACIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in PACIS 2016 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.
Mixing Consumers’ Rationality and Sociality: Effects of Product Quantity and Popularity Information on Online Shopping

Yan Yu, Key Laboratory of Data Engineering and Knowledge Engineering (MOE), School of Information, Renmin University of China, Beijing, China, yanyu@ruc.edu.cn

Chuanqi Wang, School of Information, Renmin University of China, Beijing, China, wangchuanqi_ruc@163.com

Keyi Luo, School of Information, Renmin University of China, Beijing, China, lky1994417@163.com

Ben Liu, Department of Information Systems, City University of Hong Kong, Hong Kong S.A.R., ben.liu@cityu.edu.hk

Abstract

Classical economical theories assume whatever information is available about products will be fully and efficiently processed by consumers, thus the increase of information amount would lead to greater diversity of decisions. However, consumers’ information processing capacity is limited. A large amount of product alternatives that requests consumers’ intensive cognitive effort will activate their social learning by switching decision strategy and relying on the information of product popularity. Thus, this experimental study attempts to discover the mixture of consumers’ rationality and sociality in online shopping. A 2*2 factorial design was conducted to tease out the effects of choice set and product popularity on individuals’ cognitive efforts and preference reversal, as well as the effects on the market structures that are aggregated from individual decisions. The experimental results demonstrate that, despite a large amount of product alternatives, participants may not always invest abundant cognitive efforts and the market is more concentrated with the presence of product popularity. Theoretical and practical implications are discussed.

Keywords: Cognitive effort, Social learning, Preference reversal, Market structure.
1 INTRODUCTION

A main attraction of interactive electronic retailing for consumers is to reduce their search costs for products and product-related information (Alba et al. 1997; Bettman et al. 1991). The search costs include the time that consumers spend as well as cognitive effort that consumers need to invest. Thus, the presence and presentation of product-related information play an critical role in reducing consumers’ search costs and cognitive efforts, therefore accelerating their online purchase decision.

On one hand, online shopping environments allow retailers to offer large amounts of product related information, therefore consumers can access information about a large number of products and a vast amount of information about each product (Parra & Ruiz 2009). Both the number of products and the number of attributes are factors that increase consumers’ cognitive load and make the purchase decision more complex (Payne 1982). Thus, the presence of decision aids such as search tools and recommendation tools have been found effective in cutting down consumers’ cognitive cost (Parra & Ruiz 2009; Wang & Benbasat 2008). When the information of products and attributes increase, consumers may use more advanced search tools (e.g., sorting) to narrow the consideration set of choices, thus reducing their cognitive effort (e.g., product comparison) in the final purchase decision.

On the other hand, online shopping environments also include public information, such as the indication of product popularity by sales rank, and the online review as well. Those public information may result in consumers’ preference reversals (Bettman et al. 1998), which question the basic assumption of rational decisions of consumers. Preference reversals occur when consumers prefer different products in different online shopping environments. Classical economic theories predict that more information will lead to a greater diversity of decisions, reflecting the diversity of individuals’ needs and preferences. These theories often assume that consumers are rational and that their information-processing capacity is unlimited (Becker 1976). However, the experimental research on real human agents’ behavior challenges this assumption by revealing that information process capacity is limited (Bettman 1979; Cowan 2000; Sasaki et al. 2011). Thus, human agents sometimes have cognitive overload, which is referred to the quantity of information available exceeding processing capacity (Schwartz 2005). Facing the unprecedented amount of product information online, consumers may focus on only a few facets of the information available and frequently rely on mental shortcuts and simple heuristic strategies (Payne et al. 1993). Public information therefore becomes crucially important, as it is the source that leads consumers to simplify their decision process and thus resulting in preference reversals. Consumers tend to rely on what other people have chosen, which is called “social learning” (Boyd & Richerson 1982; 1985; Efferson et al. 2008) or “herding behavior” (Gwynne 1986; Keynes 1936; Scharfstein & Stein 1990), although those choices may not perfectly fit to their own preferences. Sasaki et al.’s (2011) experiments have demonstrated that the presence of too much product information would lead consumers to draw upon popularity information, resulting in the increase of the clustering of consumers’ choices of the most popular product.

Regarding the fact that popularity information and a large quantity of product information are available on many online shopping sites (e.g., Amazon.com, JD.com, et al.), it is worthy of examining the effects of those information on consumers’ information processing and the final purchase decision.
At the initial stage, consumers is assumed to be economically rational to choose the optimized products which is in line with their preferences; however, when consumers are exposed to a large amount of product information, they probably switch their strategy to simplify their heuristics and conform to the choices of others, although the purchase decision may not be consistent with their initial preference. However, few of prior research has gouged the mixture effects of information quantity and popularity of products on consumers’ preference reversals that are resulted from the enlarged cognitive load.

Apart from the examination of effects of different shopping environments on individuals’ purchase decisions, it is even important to examine how disclosure of product information affects the market structure. Sasaki et al.’s (2011) experiments demonstrate that more information of products will lead consumers’ decisions to become less diverse, thus the overall market is more concentrated. The social learning effect becomes salient, when consumers have to invest a large amount of cognitive effort in decision making. Consumers’ social learning and herding behavior will result in a less diverse but more concentrated market structure. Brynjolsson et al. (2006; 2010; 2011) have discussed the creation of “Long Tail” in online shopping sites, where search tools play a central role in the increase in the supply and demand of niche products. At the same time, many markets can be increasingly described as “Superstar” or “Winner-Take-All” markets where blockbuster products dominate sales (Fleder & Hosanagar 2009). However, the economic analyses cannot reveal the underlying psychological mechanism of the formation of a long tail market with diversified sales distribution or a superstar market with a concentrated sales distribution. Lowering consumers’ search cost may lead to a long tail market, however, consumers’ social learning and herding behavior will heighten the kurtosis of distribution, resulting in a thinner tail. Therefore, this study goes further to examine the effect of product information quantity and popularity on the online shopping market structure, which is an aggregation of individuals' purchase decisions.

2 LITERATURE REVIEW AND THEORETICAL BACKGROUND

In this section, we review three streams of literature: (1) the research of human’s information processing capacity and rational decision making strategy, from which we know how consumers’ cognitive load are created and how consumers invest their cognitive efforts; (2) social learning theory which provides a social view of consumers’ herding behavior during their decision making; (3) the research of market structure of an electronic market or online market.

2.1 Literature of Information Processing and Cognitive Load

An important assumption in classic economics is that consumers have infinite ability of processing information so the greater information set will produce more various decisions and more likely to reflect the preference of individuals (Becker 1976). But a considerable number of theoretical and empirical studies indicate that consumers have finite limits to absorb and process information (Bettman 1979; Cowan 2000; Miller 1956). Bettman et al. (1991) summarize six types of decision-making strategies, including the weighted additive, equal weighted additive, lexicographic, elimination by aspects, and the majority of confirming dimensions strategies. Among the various decision making strategies, Wang & Benbasat (2009) futher condense into three types of decision strategies, including
additive-compensatory based strategy, elimination based strategy and hybrid strategy. An elimination based strategy eliminates the items if strategy doesn’t set cutoff levels for attributes but accumulates the value of all attributes. A hybrid strategy is a mixture of the aforementioned two strategies, in which an individual eliminates items when its “essential attributes” don’t meet requirements and then uses additive-compensatory based strategy for the rest of items. From the assumption of rationality of consumers, the weighted additive strategy is preferable, as consumers tend to consider values of each alternative on all relevant attributes, resulting in a large amount of cognitive effort. This strategy involves consumers’ substantial computational processing of information.

When the consumers are provided with too much information which exceeds their processing limit, they will adopt simpler strategy for decision making. Schroder et al. (1967) state a central theme that differentiation and integration in cognition and behavior increase with increasing environmental input until reaching an optimal information-processing level; however, when environmental input increases further, individuals’ information-processing capacity begins to decrease. A number of research also present the superfluous information would impede consumers from making optimal decisions (Bettman et al. 1991; Jacoby et al. 1974; Scammon 1977). In investigating the effect of quantity of information on consumers’ decision making, Jacoby and his associates conducted pioneering research by varying the brand choices and the number of attributes per product to control information load and examining its effect on decision-making performance (Jacoby et al. 1974). They assumed that consumers are optimizer, however, they found the dysfunctional consequences of the consumers when the information load increased and the subsequent cognitive load increased for the consumers.

2.2 Social Learning Theory and Herding Behavior

Observational learning or social learning is one of the most ubiquitous means of decision making, which occurs when one observes others’ behavior and infers something about the usefulness of the behavior based on the observation (Banerjee 1992). Decisions which are fraught with complexity and uncertainty are prone to observational learning. The herding behavior, as a phenomenon resulting from observational learning, has been intensively studied in adoption of novel technology and investment. Banerjee (1992) has done the pioneering work in herding behavior by building a simple probability model, where a sequence of Bayesian individuals make once-in-a-lifetime decisions under incomplete and asymmetric information. He proposes that an agent tends to choose the ones that are the concentrated decisions by other agents when lacking the signal of the right choice. Even though the agents are provided with private information which is supposed to a difference choice, individuals eventually imitate their predecessors (Banerjee 1992; Bikhchandani et al. 1992). This implies that in a social context, individuals may have a social rationality while not economic rationality by following the herd while ignoring their originally concerned information.

Different factors may cause herding behavior in various fields. In management science, Keynes (1936) suggests that professional managers will follow the herd if they are concerned about how others will assess their ability to make sound judgment. Similarly, Scharfstein & Stein (1990) suggest that reputation concerns and unpredictable components to the outcomes can raise herding behavior. Social learning theory has also been applied to individuals’ online behavior in e-commerce context. Since human information processing capacity is limited (Bettman 1979; Miller 1956), the information
quantity can exceed processing capacity sometimes, which is referred to as cognitive overload by Schroder et al. (1967) and Schwartz (2005). When a state of cognitive overload occurs, decision makers will focus on only a small part of information and rely on simpler decision strategies (Einhorn 1970; Tversky 1972), one of which is imitating others’ choices (Boyd & Richerson 1982; Efferson et al. 2008). Once decision makers in online shopping adopt social learning strategy, preference reversal is more likely to appear.

2.3 Market effect: Long tail vs. Superstar in online marketplace

When the individuals’ decisions are aggregated, different market structures are formed and emerge. Improvements of information technology are truly transforming both consumers and producers’ behavior in market. A “Long tail” in the distribution of product sales is created because of the increase in the supply and demand of niche products. Brynjolfsson et al. (2010; 2011) offer two basic explanations for the Internet’s long tail phenomenon from supply side and demand side. On the supply side, IT enables internet channel to carry a much larger product selection than traditional retail channel. By increasing the supply of niche products that are unavailable through traditional channels, Internet commerce may boost the share of sales generated from niche products and thus creates a long tail. On the demand side, IT, enabled search, discovery tools and recommendation systems, allows consumers to acquire product information with greater convenience and lower cost. By contrast, offline shoppers do not search deeply simply because of the inconvenience of locating a niche product among thousands of goods. Although the long tail phenomenon shows that product sales are more evenly distributed in internet commerce, the Superstar products still exist in this situation (Brynjolfsson et al. 2010; 2011). One of the explanations to this phenomenon on demand side is that consumers may want to have social interactions with other consumers. They may use product sales as a signal of quality or limit their consideration set to economize on cognitive load.

Classical economic theories predict that more information will lead to a greater diversity of decisions and they assume whatever information is available about products will be fully and efficiently processed (Becker 1976). However, the recent research (Sasaki et al. 2011) shows that the the increasing amount of attribute information leads to individuals’ buying the popular product alternative, resulting a more concentrated market but a less diversified market with various decisions. Parra & Ruiz (2009) points out that amount of information about alternatives and attributes (as well as search tool) transform consumers’ way in consideration sets, resulting in consistence result with their preference, integrated by more equally preferred alternatives. Consumers do feel more satisfied and less confused with more information, but once the quantity of information surpasses human’s cognitive limits, behavior tends to become confused and dysfunctional. It would lead to substantial ramifications for marketers, legislators, and other public policy makers (Jacoby et al. 1974).

3 RESEARCH MODEL AND HYPOTHESES

Based on the above literature review and the theories of cognitive load and herding behavior, we develop a research model shown in Figure 1. In this research model, we aim to examine the effects of public shopping environment versus private shopping environment on individuals’ purchasing
decision making (including individuals’ cognitive loads and their preference reversals), as well as the aggregated effect of different environments on the market diversity or concentration on the opposite.

**Figure 1. Research Model**

3.1 **Effects of choice set and product popularity on individual cognitive effort**

According to Bettman and his associates (1991), individuals’ cognitive load increase with the increase of options in a choice set. When consumers face a large choice set, they need to invest more cognitive effort to make decisions. Cognitive effort is a function of the number of elementary information processes. A decision rule or strategy is represented as a sequence of mental events, such as reading a piece of information into short-term memory, multiplying a probability and a payoff, or comparing the value of two alternatives on an attribute (Bettman et al. 1991; Newell & Simon 1972). In a large choice set, individuals need to read more products and attributes as well do more attribute-based comparisons among alternatives. Individuals may also use search tools or decision aids to reduce their search cost, which thus eliminates their cognitive effort for decision making (Brynjolfsson et al. 2011). One typical function search tool is the sort function. Individuals can perform an elimination strategy by several rounds of attribute-based sorting to get a smaller consideration set for decision making. Consistently, in a large choice set that requests more information processing and computing, consumers will perceive more cognitive effort required for tease out an optimal alternative. Thus, we hypothesize that:

_Hypothesis 1:_ **Consumers will invest more cognitive effort (e.g., compare, read, and sort) and perceive a higher level of cognitive effort when buying products in a large choice set than in a small choice set.**

According to social learning theory and herding behavior research, individuals have an propensity of following others’ behavior while neglecting those information which they are concerned about (Banerjee 1992; Bikhchandani et al. 1992). When performing an online shopping in a public environment where the product popularity are present, individuals may switch to rely on such public information to make a decision. The public information of product popularity is critical to consumers, when they face a large amount of information to process or face uncertainty in decision making. Based on the information processing theory, individuals often feel confused and uncertain when information
available exceeds their information processing capacity (Bettman et al. 1991; Jacoby et al. 1974; Scammon 1977); and therefore individuals rely more on public information while ignoring their private information (Sasaki et al. 2011). Thus, the product popularity information is especially important when consumers need to make a decision in a large choice set. As the consumers switch to a simple decision strategy via social learning from others, they invest less cognitive effort in such public environment with product popularity presence than in the private environment where consumers still need to make decisions based on attribute-based information processing. Thus, we hypothesize that:

**Hypothesis 2:** Consumers will invest less cognitive effort (e.g., compare, read, and sort) and perceive a lower level of cognitive effort in the public shopping environment where product popularity information is present, comparing with the private shopping environment where the product popularity information is absent.

### 3.2 Effects of choice set and product popularity on preference reversal

Dysfunctional consequence is defined as the bias of the consumer decision from best choice (Jacoby et al. 1974; Schroder et al. 1967). In particular, preference reversal is concerned in this study. Consumer preferences can be formed in different ways. In some cases, buyers directly compare alternatives across various attributes and choose the one they most prefer. In other situations, consumers evaluate each option separately and then pick the one that is judged most favorably. It has traditionally been assumed in marketing and decision research that preferences are invariant across such preference formation and elicitation methods (Tversky et al. 1988). Preference reversal has been studied from the compatibility perspective (Maciejovsky & Budescu 2013; Nowlis & Simonson 1997), but we expect the size of choice set and the information of product popularity will also have effect on consumers’ preference reversal. It is noteworthy that the preference reversal in this study is about the degree of inconsistency between consumers’ preferred (best/optimal) product alternative and the final purchased alternative. That is, the best option is defined as that option of the n options presented to the individual which most closely approximated to the "ideal" option (Jacoby et al. 1974).

Prior studies have proven that individuals’ decision quality increases with more available information until it exceeding information processing capacity (Schroder et al. 1967). This implies that the decision will be significantly deviated or even biased when consumers have information overload. Jacoby et al. (1974) regard the consumers as optimizers and measure the best choice as well as dysfunctional consequence accordingly. Specifically, the empirical investigation revealed dysfunctional effects of information overload if the respondents were provided with ten or more alternatives in the choice set or with information on over fifteen attributes (Miller 1956). Therefore, preference reversal is more likely to occur and such reversal is more deviated when consumers purchase products in a large choice set. Thus, we hypothesize that:

**Hypothesis 3:** Consumers’ preference reversal is more deviated when they do online shopping in large choice set than in small choice set.

According to social learning theory, consumers are likely to rely on the product popularity information rather than invest a large amount of cognitive effort in attribute-based information computing (Banerjee 1992; Bikhchandani et al. 1992). In some scenarios, consumers’ preferring options may not be the same as the most popular one. Therefore, consumers may buy a different product from what they
originally want by following others’ decisions, resulting in the preference reversal. Such preference reversal is even more likely to occur when consumers have a high level of cognitive load and the product popularity information presents at the same time. In such a scenario, consumers tend to switch their decision strategy to rely on public information while not personally concerned information. Furthermore, the inconsistency between the preferring option and the popular option may increase consumers’ confusion and uncertainty. The presence of product popularity such as sales and rank will increase consumers’ preference reversal. Such effect is even salient when consumers are requested to process a large amount of attribute-based information. Thus, we hypothesize that:

Hypothesis 4: Consumers’ preference reversal is more deviated in a public shopping environment with product popularity presence than in a private shopping environment with product popularity absence.

3.3 Effects of choice set and product popularity on market structures

According to decision strategies (Bettman et al. 1991), ideal decisions should be fit to consumers’ preference. We reasonably assume that different people have different preference, thus their decisions should be diversified. But when social learning commences, consumers tend to imitate precedents’ behavior while giving up their own preference. Thus, consumers’ social learning via relying on the product popularity information is likely to result in the concentration of their decisions, i.e., a concentrated market structure or a thin tail. Although a large choice set with more options is expected to generate a long tail (Brynjolfsson et al. 2006; 2010; 2011), the superstar market is still like to emerge when the product popularity significantly influences individual consumers’ preference reversal and force them to herd. In fact, when individual face with a high level of cognitive load and uncertainty, social learning effect become salient, which lead to a concentrated market where consumers choice converge. On the opposite, in small choice set where the available information doesn’t exceed consumers’ information processing ability, social learning may not be activated and individual consumers purchase based on their own preferences, thus resulting in more diverse market structure. Thus, we hypothesize that,

Hypothesis 5: The market structure aggregated from individual consumers’ decisions is more concentrated when the shopping environment has a large choice set and product popularity information than in other conditions.

4 METHODOLOGY

4.1 Experiment Design

A 2 by 2 factorial experiment was adopted to assess our research model and hypotheses. The experiment setting is shown in Table 1. The experiment was in a within-subject design, in which each subject was asked to experience four treatments. We designed an online shopping website named as “AiGou” (love shopping) for experiment. The website provided four different kinds of products, including Humidifier, Polaroid, Earphone and Voice recorder. We provided different scenarios to trigger subjects to buy these products. Each kind of product had eight attributes that were scored in 10-point scale. Instead of using the text to describe the attribute, we used the score to quantify how well each product performed in different attribute, thus the subjects could tease out the
optimal choice based on the score calculation if they were completely rational. All products were on sale in a real shopping website, thus we assigned the score to each attribute of the product to align with the reality.

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Public Shopping Environment (Sales and rank information presence)</th>
<th>Private Shopping Environment (Sales and rank information absence)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large choice set</td>
<td>Treatment A</td>
<td>Treatment B</td>
</tr>
<tr>
<td>(20 alternatives, 160 attribute scores)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small choice set</td>
<td>Treatment C</td>
<td>Treatment D</td>
</tr>
<tr>
<td>(4 alternatives, 32 attribute scores)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Table 1. Experiment settings*

### 4.2 Participants, Tasks and Counterbalance Method

We recruited university students (n=58) to participate in our experiment to buy four kinds of products in four different treatments with different sequences. The experiment lasted around 40 minutes on average. All clicking behavior of participants were automatically stored, which was for analyzing the objective cognitive efforts, preference reversals, and market structures. All participants were rewarded with RMB30 and 10 percent of them were rewarded with additional RMB100 by luck-draws. Among the participants, 41% were male, 49% were female. The mean age was 19.3 years old. All participants indicated that they had online shopping experience, and 83% of them had such experience over one year. Furthermore, 35% of the participants would shop online at least once per week, 67% of them would do 1-2 times online shopping per month, and around 8% of them would shop online in lower frequency.

Regarding the within-subject experimental design, we took serious precautions to minimize the learning effect and fragility in the experiment. First, we asked participants to buy four different kinds of products as aforementioned. Second, we counterbalanced the sequence of treatments for subjects. We created a counterbalance matrix to assure 58 participants were randomly assigned to the to eight different groups: (1) each treatment appeared an equal number of times in each position in the sequence, (2) each treatment preceded and followed every other treatment an equal number of times, and (3) each treatment paired with every experimental product and each pairing of treatment and product showed up an equal number of times.

### 4.3 Measures

*Cognitive efforts* that invididuals invest in online shopping shape their cognitive load for decision making and are shaped by their behavior, e.g., click behavior stream. Objectively, we measured cognitive effort by calculating the frequency of individuals’ reading the attributes (i.e., the sum of all clicks of attribute-based items), frequency of comparing the attributes of different items, frequency of using the sorting tool on the website. The percieved cognitive efforts were measured by assessing their subjective psychological states (Jacoby et al. 1974). Nine questions about individuals’ confidence on product, confidence on information and the cognitive effort perception were asked in a 7-point Liket scale. Sampling questions include “I am certain that I made the optimal decision”, “I hope to get more information about this kind of product”, “To get the item, it requires me great effort” and so on.
Preference reversal is a reflection of individuals’ dysfunctional consequences of decision making strategy switching. Therefore, we calculated the distance of inconsistency between individuals’ preferred alternative and the final purchased alternative. In specifically, we first teased out the optimal alternative based on individuals’ preferences. In order to achieve that, all participants were asked to rate the given attributes in a 7-point Likert scale and the ratings were treated as weight of the attributes for decision making. All given alternatives had scores based on participants’ weighted preferences. The alternative with the highest score should be considered the optimal choice. Thereafter, we calculated the distance or score gap between the preferred optimal alternative and the final chosen alternative. Although prior research only discuss preference reversal as inconsistency of options, we further quantify the degree of such reversal.

Market structure is accessed by its concentration or diversification on the opposite. We adopted Gini Coefficient to measure the concentration or diversity of the participants’ decisions. To calculate the Gini coefficient, we follow the steps: (1) rank the items by the sales volume from the highest to the lowest; (2) calculate the proportion of every item; (3) use the Gini coefficient formula to get the results.

5 RESULTS AND DISCUSSION

Before the hypotheses testing, we assessed the reliability and validity of the constructs of subjective cognitive efforts that were measured by multiple items. The subjective cognitive efforts were composed by confidence on product, confidence on information, and the perceived cognitive effort. The Cronbach’s α values of the three constructs were 0.872, 0.714 and 0.812, respectively, exceeding the threshold of 0.7 (Nunnally 1978). The loadings of items were above 0.6, providing the evidence for convergent validity; the items loaded on the corresponding constructs, indicating acceptable discriminant validity. The descriptive statistics of dependent variables are shown in Table 2.

<table>
<thead>
<tr>
<th></th>
<th>Treatment A</th>
<th>Treatment B</th>
<th>Treatment C</th>
<th>Treatment D</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective Cognitive efforts</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compare</td>
<td>6.933 (4.536)</td>
<td>6.690 (4.135)</td>
<td>8.926 (6.768)</td>
<td>6.793 (4.994)</td>
</tr>
<tr>
<td>Read</td>
<td>134.117 (88.281)</td>
<td>132.776 (82.767)</td>
<td>35.759 (25.92)</td>
<td>28.019 (18.269)</td>
</tr>
<tr>
<td>Sort</td>
<td>0.383 (0.143)</td>
<td>0.138 (0.146)</td>
<td>0.362 (0.146)</td>
<td>0.259 (0.151)</td>
</tr>
<tr>
<td><strong>Subjective cognitive efforts</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Confidence on product</td>
<td>5.083 (0.141)</td>
<td>5.172 (0.143)</td>
<td>4.963 (0.149)</td>
<td>4.953 (0.150)</td>
</tr>
<tr>
<td>Confidence on information</td>
<td>4.608 (0.198)</td>
<td>4.586 (0.201)</td>
<td>4.509 (0.208)</td>
<td>4.689 (0.210)</td>
</tr>
<tr>
<td>Perceived cognitive effort</td>
<td>3.311 (1.257)</td>
<td>3.276 (1.398)</td>
<td>3.389 (1.364)</td>
<td>3.277 (1.245)</td>
</tr>
<tr>
<td><strong>Dysfunctional consequence</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preference Reversal</td>
<td>47.245 (5.234)</td>
<td>49.606 (5.323)</td>
<td>53.159 (5.517)</td>
<td>71.016 (5.569)</td>
</tr>
</tbody>
</table>

*Table 2. Descriptive Statistics of Dependent Variables by Treatments*

Next, we conducted a series of MANOVA to test the effects of public vs. private shopping environments, large vs. small choice sets, and their interaction effects on individuals’ online shopping decision making (see Table 3).
<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>MANOVA Tests</th>
<th>Tukey tests</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Overall</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compare</td>
<td>E: F=2.963, p = 0.087*</td>
<td>TC&gt;TB (p=0.104*)</td>
</tr>
<tr>
<td></td>
<td>C: F=2.302, p = 0.131</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E × C: F=1.872, p = 0.173</td>
<td></td>
</tr>
<tr>
<td>Read</td>
<td>E: F=0.283, p = 0.595</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=141.582, p = 0.000***</td>
<td>TA&gt;TC, TB&gt;TD,</td>
</tr>
<tr>
<td></td>
<td>E × C: F=0.141, p = 0.708</td>
<td>TA&gt;TD, TB&gt;TC</td>
</tr>
<tr>
<td>Sort</td>
<td>E: F=1.248, p = 0.265</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=0.101, p = 0.751</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E × C: F=0.280, p = 0.597</td>
<td></td>
</tr>
<tr>
<td>Preference reversal</td>
<td>E: F=3.488, p = 0.063*</td>
<td>TD&gt;TC (p=0.079*)</td>
</tr>
<tr>
<td></td>
<td>C: F=6.371, p = 0.012***</td>
<td>TD&gt;TB (p=0.021***)</td>
</tr>
<tr>
<td></td>
<td>E × C: F=2.049, p = 0.154</td>
<td>TD&gt;TA (p=0.007***)</td>
</tr>
<tr>
<td><strong>Humidifier</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compare</td>
<td>E: F=7.003, p = 0.011**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=0.776, p = 0.382</td>
<td></td>
</tr>
<tr>
<td>Read</td>
<td>E: F=2.803, p = 0.100*</td>
<td>TA&gt;TC (p=0.060*)</td>
</tr>
<tr>
<td></td>
<td>C: F=35.452, p = 0.000***</td>
<td>TA&gt;TC (p=0.000***), TB&gt;TD (p=0.015**), TA&gt;TD (p=0.000***), TB&gt;TC (p=0.001***)</td>
</tr>
<tr>
<td>Percieved cognitive effort</td>
<td>E: F=0.434, p = 0.513</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=2.686, p = 0.107*</td>
<td></td>
</tr>
<tr>
<td><strong>Polaroid</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Confidence on product</td>
<td>E: F=0.998, p = 0.322</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=2.762, p = 0.102*</td>
<td></td>
</tr>
<tr>
<td>Confidence on information</td>
<td>E: F=0.276, p = 0.602</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=3.188, p = 0.080**</td>
<td></td>
</tr>
<tr>
<td><strong>Voice recorder</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sort</td>
<td>E: F=0.468, p = 0.497</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C: F=3.675, p = 0.061*</td>
<td></td>
</tr>
<tr>
<td><strong>Earphone</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preference reversal</td>
<td>E: F=0.374, p = 0.544</td>
<td>TD&gt;TB (p=0.020**)</td>
</tr>
<tr>
<td></td>
<td>C: F=8.856, p = 0.004***</td>
<td>TD&gt;TA (p=0.015***)</td>
</tr>
<tr>
<td></td>
<td>E × C: F=1.904, p = 0.173</td>
<td></td>
</tr>
</tbody>
</table>

Notes: * p ~0.10; * * p < 0.10; ** p < 0.05; *** p < 0.01; E: Public vs. Private Environments; C: Large vs. Small Choices; TA: Treatment A; TB: Treatment B; TC: Treatment C; TD: Treatment D

Table 3. Summary of MANOVA tests and Turkey tests

Overall, we find that shopping environments and the size of choice set exert main effects on individuals’ purchase decision making. We first check the effects of treatements on cognitive efforts. When the choice set is large, participants invest more cognitive efforts in reading the attributes of product alternatives (F[1,223] =141.582, p<0.000). When participants are involved in the public shopping environment with sales and rank information presence, they invest more cognitive efforts in comparing the alternatives (F[1,223] = 2.963, p<0.087), while not switching to a simpler strategy of relying on the public information as expected. A plausible reason is that the large choice set of 20 alternatives and 160 attributes may not present high cognitive load for participants. This can be confirmed by the insignificant differences of the subjective cognitive efforts across four treatments. Although reading, comparing, sorting 20 alternative and 160 attributes have been suggested already exceeding individuals’ information process capacity, participants may pay selective attentions on particular attributes, which can be conformed by their low frequencies of click actions. In particular, it is also found that the presence of public information such as sales and rank have salient influences on participants’ cognitive efforts in reading and comparing, when they perform the task of buying humidifiers. The participants perceive a higher level of cognitive efforts when they buy humidifiers.
and polariads from a large basket. This is possible due to participants unfamiliar with these products or unknowledgeable with the attributes of products, thus having stronger feeling of cognitive load.

Second, the above results show that the treatments exert effects on participants’ preference reversal, resulting in the dysfunctional consequences. The results show that the size of choice set significantly affects the degree of participants’ preference reversal \( (F_{1, 223} = 6.371, p < 0.012). \) When participants have more choices, they have more chances to buy their preferred products while not revering their preferences; however, when participants have less choices, preference reversal is more likely to occur and the inconsistency between the preferred alternative and the really purchased one may be enlarged. Further, participants have a lower degree of preference reversal in a public shopping environment than in a private environment \( (F_{1, 223} = 3.488, p < 0.063). \) It is particularly interesting to find the salience of preference reversals in the context of buying earphone. It is plausibly attributed to participants’ familiarity with this product. When individuals have stronger preferences but are given smaller choices, they will present a higher degree of deviation from preferences.

![Gini Coefficient Plots](image)

**Figure 2**: Aggregated Market Structures from purchasing options across four treatments

Third, we check the effects of different settings on the market structures aggregated from the individuals’ choices. Each treatment presents a market. Figure 2 shows the mean plots of Gini coefficients of the four different markets. Our results imply the potential, although not salient, interactions between the size of choice and shopping environments, which confirms the same convergence of market structure when public information is given as previous research (Sasaki et al. 2011). When we check the interaction effect, we also tease out such a trend, i.e, if the market grows larger with more alternatives, the market with a public shopping environment will have an
increasingly higher structural concentration and a less level of diversity of consumers’ purchase decision. Thus, the disclosure of public information such as sales and rank in a large online market is likely to form a thin tail and facilitate the formation of superstar market.

**IMPLICATIONS**

Theoretically, this research adds value to the economic psychology by teasing out the multilevel effects of information presentation on individuals’ decisions as well as the market structure. We predict that facing a large amount of product alternatives, consumers would switch from rationality to sociality by relying on popularity information, which would in turn form a thinner tail of market structure where consumers choices were concentrated on the most popular items. For the effects of choice set and popularity information on consumers’ decision making, we do find that the information amount increase consumers’ cognitive efforts such as reading attribute information and comparing alternatives. We also find the presence of product popularity information would reduce the deviation between consumers’ ideal products and the merchandise they buy. This implies that consumers may converge on similar decisions because they have similar preferences and popularity information helps to confirm consumers’ decisions. It is unexpected to find that, despite the small choice set, the preference reversal is greater but the market is more concentrated in a private environment with popularity information absence than in the public environment with popularity information presence. This needs further experimental exploration, as it might be caused by that a small choice set could be a different projection of different purchasing stages. Practically, our research findings is relevant to online marketing, thus entailing implications for retailers as well as online market administrators. Now the online marketplace typically provide a huge amount of products and the retailers often provide highly detailed information about products. All these are expected to satisfy consumers’ preferences and to form a long tail of market. However, the presence of product popularity (e.g., sales, rank, review amount) would transform the market structure in which some products can gain market dominance regardless the consumers’ different preferences. despite the absence of popularity information, participants in the moderate information condition were more likely to choose the most popular item relative to those in the large information condition. For online retailers, it is helpful to use salient popularity information to attract consumers’ attention while not simply treating such information as one attribute of product. For online marketplace administrators, they can give guidance for retailers to design the interface and advertisement by providing appropriate number of product alternatives and appropriate information presentation, thus providing sustainable online environments.

**Acknowledgement**

We would like to acknowledge the supports from projects funded by Fundamental Research Funds for the Central Universities of Renmin University of China (No. 15XNQ026) and National Natural Science Foundation of China (NSFC) (No. 71331007, 71571184), and Beijing Natural Science Foundation (No. 9142010).
References


