SEARCH AND PURCHASE IN INFORMATION-OVERLOADED RETAIL ELECTRONIC MARKETPLACE: DOES PRICE AND REPUTATIOIN MATTER?

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Abstract

This study explores buyers' search and purchase behavior in an information-overloaded retail Electronic Marketplace (EMP). Two instrumental variables, i.e. number of visitors and number of sales for an item, are used to represent buyers' search and purchase behavior. Price and reputation, two of the most frequently researched independent variables in EMP studies, are considered. The relationships between the two IVs and the two DVs are verified when transaction items are of search-type and of experience-type. This study is conducted using field data collected from Taobao (the most dominant retail EMP in China). It is found that reputation has consistent positive relationships with two DVs. Price has negative effects on two DVs. However, it might have no impacts in the case of experience-type items. Conclusively, in information overloaded EMP, reputation always matters in influencing buyers' search and purchase behavior, while price only matters in the case of search-type items.

Keywords: Electronic marketplace, reputation, price, information overload, buyers' behavior.

1   INTRODUCTION

Electronic Marketplace (EMP) is independently owned, IT-enabled intermediary information system which connect many buyers and sellers (Soh, Markus and Goh 2006). In recent years, EMPs have grown rapidly and formed marvelous giant marketplaces. For example, eBay, the most famous global EMP, has approximately 276 million registered users worldwide. These users have posted a total number of 637 million new listings in the 4th quarter of 2007, i.e., averagely 6.7 million listings per day[1]. In China, with an annual sale of RMB43.3 billion in the year of 2007, the dominant retail EMP—Taobao, defeated even the sum of local Carrefour and Wal-Mart and became the 2nd largest marketplace[2].

While the dramatically huge EMPs excite buyers by offering them abundant options, not surprisingly, they simultaneously make these options being too many to choose from. To help buyers locate their

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[1] http://news.ebay.com/fastfacts_ebay_marketplace.cfm, available on 12-Mar-2008
[2] http://forum.taobao.com/forum-14/show_thread----13526587-.htm, available on 25-Feb-2008

desired item, EMPs usually offer detailed item catalogs and powerful search engines. Even though, buyers still can find hundreds or thousands of items when search from EMPs. For example, more than 2000 items were found for Apple i phone in "phones w/o service contracts" category on eBay, and more than 6000 items were found for Nokia N73 phone in "cell phone > Nokia > N73" category on Taobao[3]. When searching by a relatively "broad" keyword, the number of listings we can get is unbelievable. Generally, it is possible for buyers to be "rational" (i.e., to compare all the listed items and choose the one with highest expected utility) when there are a handful of items in the list. However, when facing thousands of items in a list, what will buyers behave? Out of the thousands items, what kinds of items will be "lucky" enough to be viewed or even purchased?

Based on the previous consideration, we propose our research question as, "in an information overloaded EMP, how will buyers' search and purchase their desired item?" In other words, what kind of items will buyers click-in and view, and what kind of items will they purchase? Literature in electronic commerce and reputation systems suggests that price and reputation are two of the most important factors influencing buyer's search and purchase behavior (Brynjolfsson and Smith 2000; Resnick et al. 2006; Yoo, Ho and Tam 2006; Baker and Song 2007). Following these suggestions, we focus on the impacts of price and reputation in this study. Specially, since existing research mostly examined the effects of reputation in auction EMP, we choose retail EMP as our research setting to extend the existing understanding of different types of EMPs. Furthermore, we also consider two types of items (i.e., search-type items and experience-type items), because it is illustrated in literature that the relationships between reputation, price and buyers' behavior are different for these two types of items (Nelson 1970; Smith 1990; Aggarwal and Vaidyanathan 2003; Hsieh, Chiu and Chiang 2005).

Examining the impacts of price and reputation on buyers' search and purchase behavior in information overloaded retail EMP is meaningful, both from academic and practical perspective. Academically, this study can benefit to the understandings of buyers' behavior in information overloaded situations, and also can contribute to the stream of reputation system research literature. Moreover, our study can offer some cues to research on buyer's choice model when given a mass of information. From a practical perspective, the result of this study can give some suggestions to the design of EMP search engine, recommending agency, and the display mechanism of listings and items. For sellers, our research findings could also be beneficial in helping them decide their pricing and other marketing strategies.

The plan of this paper is as follows. Section 2 reviews related research studies and analyzes our research questions from a theoretical perspective. Based on this review and analysis, research hypotheses are proposed. Section 3 introduces our methodology, including field data collecting from Taobao, descriptive analysis of each variable and regression models. Section 4 presents our research results. Then these research findings are discussed in Section 5, including some remarks on implications, limitations and future research. In the end of this paper, a general conclusion is given.

2 THEORETICAL CONSIDERATIONS

2.1 EMP and "information overload"

EMP offers a platform (i.e., information systems) to participants where they can exchange product offerings and prices information, and also transact with each other. Two characteristics make EMP inevitably becoming "overloaded". First, inventory in EMP is distributively held by all the sellers. EMP itself does not hold any inventory. This distributive nature of inventory allows EMP to have massive content storage and almost infinite number of listings (Zhang 2006). Second, transaction costs

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[3] 2345 items found for Apple™ i phone in "Phones w/o Service Contracts" on eBay™; 6025 items found for Nokia™ N73 phone in "Cell Phones > Nokia > N73" on Taobao™. Search conducted at 23:00 p.m. on 11-Mar-2008.

in EMP are very low, especially for sellers. Any ordinary participants can post lists of their own items, to perhaps millions of potentially interested buyers, without setting up a "brick-and-mortar" storefront and paying a large fee incurred in transactions (Zhang 2006). Besides, updating information in EMP is also convenient and instantaneous. Due to the above reasons, it is very attractive for sellers to post their listings in EMP. These characteristic generates impetus to growing of listings.

As coined by Alvin Toffler (1970), "information overload" refers to the state of having too much information to make a decision or remain informed about a topic. When a buyer faces thousands of items in a list, it seems he/she is involved in an "information overload" problem. However, the situation is even worse in EMP: when information on listings is overloaded, information on quality is lacked. In EMP, most of the conventional quality cues in shopping (e.g. observing storefront, talking with clerks and inspecting items through touch and feel) are not available (Andrews and Benzing 2007). The absent of conventional quality cues encumber buyers in collecting sufficient information on their desired items, and thus involve them into even more difficulties in making a purchase decision.

Conclusively, buyers demand appropriate amount of listings information and thorough quality information to make purchase decisions, while the information supplied in EMP is always contrary (overloaded in listings and lacked in quality). To locate and purchase their desired items in the overloaded listings, buyers can use several strategies. One most useful strategy is to narrow down their options according to some criteria, and then selectively view some items. Intuitively, the criteria which buyers will consider in purchasing commonly will be price and quality. Empirical studies of online auctions have found that quality can be signaled by seller's reputation (Melnik and Alm 2005; Dewally and Ederington 2006; Josang, Ismail and Boyd 2007). Research in electronic commerce and reputation systems also has demostrated that reputation and price are two of the most important factors influencing buyer's search and purchase behavior (Brynjolfsson and Smith 2000; Resnick et al. 2006; Yoo et al. 2006; Baker and Song 2007). Therefore, we will choose reputation and price as our interested factors.

2.2 Reputation and price

Reputation system is commonly used in EMP to signal quality (Josang et al. 2007). For example, eBay adopted a reputation system (named as "feedback forum") to reveal participant's transaction and feedback history. After each transaction, participants involved in the transaction are encouraged to rating the behavior of their counter-partners as "1" (positive), "0" (neutral) or "-1" (negative). Reputation score is accumulated based on these ratings. Empirical studies have illustrated that high reputation score can help sellers in attracting more bidders, enhancing the rate of successful transactions, and generating price premiums (Ba and Pavlou 2002; Houser and Wooders 2006; Resnick et al. 2006; Zhang 2006). According to game theory, when stimulated by the long-term benefits generated by high reputation, sellers with high reputation score will not seize short-term benefit by delivering low quality items (Dellarocas 2003). Therefore, high reputation score can "softly guarantee" high item quality and seller honesty. Considering these quality issues, when buyers intend to narrow down their options of listings, they can prefer items from high reputation sellers.

Another criterion for narrowing down a buyer's options is price. Price in online retailing is given by sellers before transaction (similar to the "Buy-It-Now" price in online auctions). Suppose two items which have exactly the same quality and different prices. Obviously, the item with lower price can generate higher utility for buyers. Hence, when quality is similar, items with low price will attract more buyers. Without considering quality issues, buyers can prefer items with low price to narrow down their listings options.

Conclusively, the criteria chosen by buyers in narrowing down their listings options are contingent on whether they have to consider quality problems. In searching and purchasing different types of items, the importance of quality issues is different. In the following subsection, we will discuss two types of items: search-type and experience-type items. This classification method is classical (Nelson 1970;

Nelson 1974) and frequently researched in electronic commerce (Aggarwal and Vaidyanathan 2003; Hsieh et al. 2005).

2.3 Search-type and experience-type items

Search-type and experience-type items were firstly differentiated by Nelson in his seminal work on economics of information and advertising (Nelson 1970; Nelson 1974). Search-type items are items with full information of dominant attributes can be acquired prior to purchase, while experience-type items are items with dominant attributes which can only be known after purchase and use (Nelson 1970; Nelson 1974; Klein 1998). In retail EMP, collecting item information before purchase mainly relies on item descriptions, pictures and other electronic cues online. Items with such kinds of attributes as dominant attributes are search-type items, for example, cell phones, mp3 players and other consumer electronics. Contrarily, items with dominant attributes which can not be easily described on webpage are experience-type items. For example, style and fitness of clothes, which requires firsthand experiences (i.e., observation and interaction experiences) in shop, can not easily be illustrated in EMP. Items with such kinds of attributes as dominant attributes are experience-type items.

For search-type items, buyers can collect dominant attributes information from descriptions online, while for experience-type items, buyers can only know the quality after receipt of items. Simply, when searching and purchasing different types of items, buyers will pay different extent of attention on quality and price information. We will discuss this in the following subsection.

2.4 EMP and information overload

As discussed previously, to search appropriate items from overloaded listings, buyers have to quickly narrow down their options. In the case of searching a search-type item, since the item information of dominant attributes are explicitly expressed online, the quality related risk is much less than in the case of an experience-type item. Because the quality of search-type item is obvious and consistent, seller's reputation may be less useful in such a case. Therefore, buyers will pay more attention to price information, and quickly narrow down their options by price. Conversely, in the case of searching an experience-type item, buyers can not observe item quality directly. It is meaningless for buyers to find a cheap item in unknown quality conditions, because the uncertainty of quality sharply decreased his/her expected utility. Thus, in such cases, buyers will prefer reputation than price as the criterion in narrowing down their options.

Based on these discussions, we hypothesize:

H1a: Price has negative relationship with the number of visitors.

H1b: Price has stronger relationship with the number of visitors in the case of search-type items than experience-type items.

H2a: Reputation has positive relationship with the number of visitors.

H2b: Reputation has stronger relationship with the number of visitors in the case of experience-type items than search-type items.

Buyers make their purchase decisions based on the items viewed. Compared with the information overloaded searching process, buyers have already narrowed down their options before they decide which item to purchase. In such conditions, buyers can be "rational", i.e., compare the price and quality of each item, and choose the one with highest utility. In other words, given the number of visitors for an item, both low price and high quality can increase sale. Similar to the discussion in the previous paragraph, buyers have to pay attention to the quality issues in the case of experience-type items than search-type items. Therefore, reputation should be a more important factor in the case of

experience-type items, while price should be more important in the case of search-type items. Hence, we hypothesize:

H3a: Price has negative relationship with the number of sales.

H3b: Price has stronger relationship with the number of sales in the case of search-type items than experience-type items.

H4a: Reputation has positive significant relationship with the number of sales.

H4b: Reputation has stronger relationship with the number of sales in the case of experience-type items than search-type items.

These hypotheses will be verified using field data collected from Taobao in the following sections.

3 METHODOLOGY

3.1 Taobao and data collection

Field data collected from Taobao were used in verifying our hypotheses. We chose Taobao as our data source for several reasons. First, Taobao is the most dominant retail EMP in China. It has more than 55 million registered users. Buyers' behavior on Taobao is very representative. Second, Taobao offers powerful search engines and detailed catalogs in helping buyers locate their desired items. Third, buyers can reorder their search result listings by price and reputation, which are the most important variables in our study.

"Nokia N73" cell phone and "female suits" were selected as search-type and experience-type items. Using the catalog information, we excluded all the items which are essentially not what we desired, for example, accessories for "Nokia N73" cell phone. We used these two types of items because they are frequently searched items in Taobao. Furthermore, the amount of listings of these two types of items was also representative in Taobao.

3.2 Variables

A self-developed spider program was used in capturing data from Taobao on 7-March-2008. We have collected 3241 listings of "Nokia N73" and 2285 listings of "female suits". At the first step, we collected information of all the listings. From the listings, we have collected item id, item name and item price (*Price*). After the first step, our spider program "clicked into" each item description page. From each item description page, we have collected the number of hours since the item was posted (*CurrTerm*), number of visitors (*CurrVisit*) and number of sales (*CurrSale*) in this period of time, the seller's reputation score (*RpSeller*) and percentage of positive ratings (*RpPercSeller*). As suggested in several empirical studies (Livingston 2005; Melnik and Alm 2005), reputation has a decreasing marginal effect, thus we use the nature logarithm of *RpSeller* plus 1 (i.e., $log(RpSeller+1)$) to represent sellers' reputation. Before conducting any analysis, we removed 5 listings in the "Nokia N73" case and 2 listings in the "female suits" case, for the data of these 7 listings are extremely abnormal. Therefore, we have totally 5519 data points, including 3236 of "Nokia N73" and 2283 of "female suits", in the data analysis process. The variables we collected are described in table 1. A simple descriptive analysis of these two groups of data is illustrated in Table 2.

3.3 Models

We used hierarchical regression analysis in testing the hypotheses (Kutner et al. 2004). Hierarchical regression method has been widely used in testing both main effects and interaction effects (Stock and Tatikonda 2008). In this study, we firstly included the control variables in the regression equations,

and then we added the price and reputation variables sequentially, in the purpose of testing main effects (H1a, H2a, H3a and H4a). In a further step, we added the interaction term of product type and main effects variables into the regression equations. Through this step, we verified the moderating effect of product type (H1b, H2b, H3b and H4b). We also examined the changed variance (changed adjusted R^2) explained by the variable(s) added in each step, to evaluate the effect of each variable we interested in.

Variables	Descriptions
DSearch	is a dummy variable; equals to 1 when the item is search type, or 0 when the item is experience type.
CurrTerm	equals to number of hours since the item was posted.
Price	is price of item given by its seller.
RpSeller	is seller's accumulated reputation score; equals to number of positive ratings minus negative ratings; only counts ratings posted by buyers.
RpPercSeller	is seller's percentage of positive ratings.
CurrVisit	equals to number of visitors who have visit the item description page since the item was posted.
CurrSale	equals to number of sales since the item was posted.

Table 1.   Descriptions of variables

	Mean	Median	Maximum	Minimum	Std. Dev.
CurrSale	0.080	0	15	0	0.548
CurrTerm	109.603	96	336	0	77.439
CurrVisit	10.485	2	1243	0	47.928
DSearch	0.586	1	1	0	0.493
Price	1456.470	2058	4990	5	1033.314
RpSeller	468.347	47	48073	0	1744.849
RpPercSeller	86.085	100	100	0	33.814

Sample size is 5519.

Table 2.   Descriptive analysis of variables

Because the dependent variables in our study are count variables, we used Poisson Regression Model in analyzing the data (Greene 2008). Poisson regression model is used in the situation when dependent variable is a discrete variable, which in most cases will equals zero, and in other cases will takes a positive value. The typical values of such a variable are zero, one, or two, but much higher values are also possible (Greene 2008). Researchers already have adopted Poisson Regression Model in examining the relationship between reputation and number of bidders, which is also a count variable (Ruiz 2004).

We used the following equation (equation 1) as the full model in analyzing the relationship between number of visitors and the independent variables we are interested in. Equations V1~V5 (see Table3) are derived from this model, by removing some variable(s).

CurrVisit = C(1) + C(2)*DSsearch + C(3)*CurrTerm + C(4)*Price + C(5)**Log(RpSeller+1)*

            + C(6)*RpPercSeller + C(7)**DSearch*Price* + C(8)**DSearch*Log(RpSeller+1)*   (1)

The regression coefficient of *Price* was used in verifying H1a, while regression coefficient of *Log(RpSeller+1)* was used in verifying H2a. Moreover, the regression coefficients of two interaction terms were used in verifying H1b and H2b. Besides our interested independent variables (i.e., *Price* and *RpSeller*) and interaction terms, we included three control variables (i.e., *DSearch*, *CurrTerm* and *RpPercSeller*). We expected the regression coefficient of *DSearch* to be positive, because the EMP is of higher risks for purchasing experience-type items, and buyers will be more intended to view and purchase search-type items in EMP. We also expected the regression coefficient of *CurrTerm* to be positive. Intuitively, the longer after an item is posted, the more visitors will be attracted. We had no expectation on the regression coefficient of *RpPercSeller*, because before "click in" each listing, buyers generally do not know its seller's percentage of positive ratings.

The following equation (equation 2) is used as the full model in analyzing the relationship between number of sales and the independent variables. Equations S1~S6 (see Table4) are derived from this model, by removing some variable(s).

$$CurrSale = C(1) + C(2)*DSsearch + C(3)*CurrTerm + C(4)*CurrVisit + C(5)*Price + C(6)*Log(RpSeller+1)$$
$$+ C(7)*RpPercSeller + C(8)*DSearch*Price + C(9)*DSearch*Log(RpSeller+1) \qquad (2)$$

Similar to equation 1, we used the regression coefficients of *Price* and *Log(RpSeller+1)* in testing the main effects (i.e., H3a and H4a), and used the regression coefficients of interaction terms in testing the moderating effects of item type (i.e., H3b and H4b). Compared to equation 1, we included one more control variable (*CurrVisit*) in this equation. Generally, buyers have to firstly visit and verify an item before they decide whether to purchase, thus *CurrVisit* will have positive impacts on *CurrSale*. The expectations of control variables' regression coefficients are similar to equation 1, except *RpPercSeller*. When buyers have already viewed the item description page, they have known the percentage of positive ratings of its seller. Obviously, the higher percentage of positive ratings is, the less risk will be involved in purchase. We expected the regression coefficient to be positive.

We used EViews 6 in conducting the regressions. EViews 6 is a powerful statistical tool in handling Poisson Regression Models. The research results are reported in the next section.

4 RESULTS

The regression results are illustrated in Table 3 and Table 4. Table 3 shows the five equations (V1~V5) generated from equation 1, while Table 4 shows the six equations (S1~S5) of equation 2. Each column except the first one, in the two tables, represents one individual equation. We have reported the regression coefficients and their corresponding significance level in each equation, and also R^2, adjusted R^2, and changed adjusted R^2 (comparing with the equation in previous column).

In Table 3, we observed significant negative regression coefficients between price and number of visitors (in equations V2~V4), except the regression coefficient in the equation with interaction term (in equation V5). The coefficient of interaction term of *DSearch* (item type) and *Price* is negative, which means the effects of price is larger (more negative) in the case of search-type item than in the case of experience-type item. Therefore, H1b is supported. Considering the significantly zero coefficient of *Price* in the equation V5, it is possible that, in the case of experience-type items, *Price* has no effect on number of visitors, while in the case of search-type items, price has significantly negative effect. Based on these considerations, we concluded that, H1a is partially supported by our data, and H1b is supported.

We also observed consistently significant positive relationship between *Log(RpSeller+1)* and number of visitors (in equation V3~V5). Thus, H2a is supported. However, opposite to our hypothesis 2b, we observed a significantly positive relationship between the interaction term of *DSearch* and *Log(RpSeller+1)*. The positive coefficient means the effect of reputation on number of visitors in the case of search-type items is larger than in the case of experience-type items. Therefore, H2b is rejected.

	(V1)	(V2)	(V3)	(V4)	(V5)
C	1.753***	2.271***	-0.143***	0.358***	0.121***
DSearch	0.260***	6.322***	5.830***	5.846***	10.851***
CurrTerm	0.004***	0.004***	0.006***	0.006***	0.006***
Price		-0.003***	-0.003***	-0.003***	0.000***
Log(RpSeller+1)			0.395***	0.422***	0.371***
RpPercSeller				-0.007***	-0.008***
DSearch*Price					-0.005***
DSearch*Log(RPSeller+1)					0.053***
R^2	0.004	0.033	0.129	0.133	0.133
Adjusted R^2	0.004	0.033	0.128	0.132	0.132
Δ Adjusted R^2	0.004	0.028	0.096	0.004	0.000

Dependent variable is CurrVisit. Sample size is 5519. Poisson regression model has been used.

* Significant at the 0.1 level;

** Significant at the 0.05 level;

*** Significant at the 0.01 level.

Table 3.   Regression Results

	(S1)	(S2)	(S3)	(S4)	(S5)	(S6)
C	-3.170***	-3.209***	-2.856***	-4.599***	-5.233***	-6.275***
DSearch	0.521***	0.397***	4.165***	4.876***	4.806***	9.119***
CurrTerm	0.003***	0.002***	0.002***	0.004***	0.004***	0.004***
CurrVisit		0.005***	0.005***	0.004***	0.004***	0.003***
Price			-0.002***	-0.002***	-0.002***	0.000
Log(RpSeller+1)				0.318***	0.299***	0.383***
RpPercSeller					0.007*	0.007*
DSearch*Price						-0.004***
DSearch*Log(RPSeller+1)						-0.097*
df						
R^2	0.002	0.028	0.013	0.106	0.110	0.134
Adjusted R^2	0.002	0.027	0.012	0.105	0.109	0.132
Δ Adjusted R^2	0.002	0.025	-0.015	0.093	0.004	0.023

Dependent variable is CurrSale. Sample size is 5519. Poisson regression model has been used.

* Significant at the 0.1 level;

** Significant at the 0.05 level;

*** Significant at the 0.01 level.

Table 4.   Regression Results

Table 4 demonstrated the regression results of equations developed from equation 2. According to our hypothesis H3a, the regression coefficients of *Price* should be significantly negative. Similar to Table

3, we observed three significantly negative coefficients and one insignificant zero. The coefficients of interaction term of *DSearch* and *Price* is also significantly negative, which means *Price* have more effects on number of sales in the case of search-type items than experience-type items. Therefore, we concluded that H3b is supported, while H3a is partially supported, because it is possible that *Price* have not effects on the number of sales in the case of experience-type items. Table 4 also reported consistently significant positive relationship between *Log(RpSeller+1)* and number of sales (in equation S4~S6), and significantly ($p<0.1$) negative relationship between the interaction term of *DSearch* and *Log(RpSeller+1)*. The negative coefficient means the effect of reputation on number of sales in the case of experience-type items is larger than in the case of search-type items. Accordingly, we concluded that H4a is supported, and H4b is weakly supported.

We summarized all the hypotheses and research results in table 5. Totally, of the eight hypotheses, four are fully supported, three are partially or weakly supported, and one is rejected. Discussions, including implications and limitations of our study will be presented in the next section, and hints on future research are also proposed.

Hypotheses	DV	IV	Hypothesized relationship	Hypothesis Supported?
H1a	number of visitors	price	-	Partially Supported
H1b	number of visitors	price	Search type> Experience type[*]	Yes
H2a	number of visitors	reputation	+	Yes
H2b	number of visitors	reputation	Experience type > Search type[*]	No
H3a	number of sales	price	-	Partially Supported
H3b	number of sales	price	Search type> Experience type[*]	Yes
H4a	number of sales	reputation	+	Yes
H4b	number of sales	reputation	Experience type > Search type[*]	Weakly Supported

is the comparison of effect sizes (without considering directions) in the two cases.

Table 5.   Summarization of hypotheses and findings

5   DISCUSSION

5.1   Implications

One of the most important implications of our study has to do with buyers' behavior when they face overloaded information in retail EMP. As we illustrated previously, contemporary EMPs have already become marvelously huge. However, researchers merely consider the situation of information overload. Using two instrumental variables (number of visitors and number of sales), we examined buyers' search and purchase behavior in an information overloaded situation. Moreover, we distinguished the type of items, and researched its moderating effect on these relationships. The research findings clearly demonstrated that buyers will selectively view and purchase items from high reputation sellers. They are also inclined to search and purchase low price items in the case of search-type items. However, price may not be an important factor in influencing both buyers' search and purchase behavior in the case of experience-type items. Knowledge on the important criteria by which buyers narrow down their options and make purchase decisions can give some hints on the design of search engines (Berghel 1997), information agency (Berghel 1997) and recommendation agents (Aggarwal and Vaidyanathan 2003). The design of information searching and recommendation mechanisms in EMP platform is meaningful from both from theoretical and practical perspective. A

well designed EMP platform can increase users' perceived usability and usefulness of EMP, thus will attract more users to join (Gefen, Karahanna and Straub 2003). Furthermore, although this particular study focuses on buyers' behavior in information overloaded retail EMP, it also gives some hints on research in the cases of auction EMP. In auction EMP, research questions could probably similar: what kind of factors will influence buyer's search and bidding behavior when they face hundreds or thousands of auctions? Are these relationships contingent on item type? We expect the effect of reputation will still be significant, but the effects of price (which could be start bid or current highest bid) should be reconsidered.

The second implication of our study is that we verified the effects of reputation system in the circumstance of retail EMP. Reputation is expected to have positive relationships with transaction outcomes theoretically (Dellarocas 2003), but empirical studies have found some mixed results (Wan and Teo 2001; Eaton 2002; Gilkeson and Reynolds 2003; Zhang 2006). Most of these empirical studies focused on auction EMPs, especially eBay. Effects of reputation in other settings are seldom examined. In this study, we tested the effect of reputation using data collected from Taobao, which is a retail EMP in China, and found consistent positive impacts of reputation on both number of visitors and number of sales. Therefore, our findings affirmed the theoretical expectation of the positive effects of reputation from a different perspective.

The third implication of this research is related to the understandings on effects of price and pricing strategy. Price is given before purchase in retail EMP, rather than decided by bidders in auction EMP. According to economic theories, a cost occurs when a seller want to develop a high reputation, thus the seller will try to seize price premium as payback (Dellarocas 2003). However, in retail EMP, if sellers try to charge a high price, they may lose some potential buyers; and this effect is contingent on the type of items they sell. In other words, a high price strategy will be more effective when sellers are selling experience-type items rather than search-type items. Our study sheds some lights on studies related to seller's pricing behavior online. Practically, sellers can utilize our findings when they sell different types of items. For example, if they sell search-type items, they can moderately charge a low price to attract buyers; but when they sell experience-type items, since buyers are not sensitive to price, they can charge a price premium as their payback of investment on reputation.

5.2 Limitations and future research

There are several limitations in this study. First, in the information overload situation, say, facing thousands of listings, buyers can only view a little portion of these listings. The most commonly happened situation is, buyers reorder the listings by their interested criteria, and only view the first several pages. To attract more buyers, experienced sellers will pay more attention on the description (such as include discount information in the item title) of items in listings. A carefully designed listing will possibly increase buyers' desire of "click in" (GE, TEO and LEE 2002). Experienced sellers may also have other special methods in attracting buyers to "click in". These special methods could be advertisements on some online forums, auto item recommendations and customer relationships management through "Wangwang"[4] (Ou and Davison 2007). These omitted variables might be the reason why the power of our model is relatively small. Further study should include these omitted variables, such as the additional options in the listings (GE et al. 2002), description of items, pictures, escrow service and payment choice (Baker and Song 2007). Especially, IM tools combined with EMP (e.g., Wangwang on Taobao, Skype on eBay) can help in managing customer relationships (Ou and Davison 2007), and even attracting and making deals. Examining the effects of IM tools on buyers' behavior could also be an interesting topic in future.

Second, other than item price and quality, buyers may also consider sellers' trustworthiness and service quality when they searching for items. For example, they probably will consider whether seller

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[4] An IM tool combined with Taobao retail EMP.

will carefully pack and quickly deliver the item. Because reputation is correlated with seller's experience (McDonald and Slawson 2002), reputation score is not only a signal of seller honesty, but also a signal of seller's service ability. Buyers may probably be more intent to purchase from experience sellers for their nice service quality. Future research should try to distinguish seller trustworthiness and item quality, and study the relationship between reputation and these two constructs individually.

Third, since quality of experience-type items is unknown before purchase and use, it is unavoidable that such kinds of items have various values. Contrarily, search-type items are more likely to have consistent quality and value. We used "female suits" to represent experience-type items and "Nokia N73" to represent search-type items. Unavoidably, two questions remained related to the data. Firstly, using "female suits" and "Nokia N73" to represent experience-type items and search-type items is relatively subjective. Secondly, the listings of "Nokia N73" have relatively less variance on price while the listings of "female suites" have more variance on price. Future study should collect more data, and verify the hypotheses in more situations. Besides, gender could also be one reason of the observed different behaviors, because a majority of the visitors and buyers of "Nokia N73" should be male, while visitors and buyers of "female suites" should always be female. Future research also should consider this problem.

6   CONCLUSION

The purpose of our study is to explore buyers' search and purchase behavior in an information-overloaded retail EMP. We focus on the effects of two commonly researched variables (i.e., price and reputation) when items are of different types (i.e., search-type and experience-type). Using field data collected from Taobao, we find that reputation always matters in influencing buyers' search and purchase behavior, while price only does in the case of search-type items.

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