An Empirical Investigation Into the Use of Heuristics and Information Cues by Bidders in Online Auctions

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INTRODUCTION

Researchers in a number of disciplines recognize that individuals possess a limited information-processing capacity. Individual capacity to process information depends on the cognitive abilities of the individual, and the form, quantum and type of information that is presented. Individual cognitive limitations lead to different strategies for dealing with information, and differing outcomes. Especially when faced with high levels of uncertainty, large volumes of information, and low outcome valency, empirical evidence suggests that individuals tend to use simple decision rules that quickly and cheaply reduce the incumbent cognitive strain. Psychologists and cognitive scientists study the heuristics that people use to deal with overwhelming information. Information scientists focus on the structure and positioning of these cues, and the reasons for their importance in decision making. The current study takes an information-processing view of bidder behaviour under uncertainty, and focuses on the choice, and resultant impact of heuristics on auction participation and values.

Auctions, whether traditional or electronic, involve high levels of uncertainty to their participants. In any web-based auction, sellers foster a level of uncertainty, by revealing limited information, thereby intending to create a valuation gap in the minds of potential bidders. Buyers in a bid to maximize utility, use the seller-specified information to place bids, intending to procure the product at their lowest valuation. However, bidders have to choose from among competing listings that vary in the amount of information that sellers provide. Hence, economic theory characterizes bidding as a highly uncertain process, with bidders in any auction facing three levels of uncertainty: first, an uncertainty about the quality and value of the product being auctioned; second, an uncertainty about the strategy to be used to win the auction; and third, an uncertainty about the valuation of other bidders and their winning strategies Feldman and Mehra 1993; Laffont 1997). Hence, the online auction presents an ideal decision scenario to test for the choice and impacts of heuristics in decision making. The study is organized as follows: the first section covers the pertinent literature on heuristics and information processing, and the research questions. The second section presents the methodology, followed by the procedures, the analysis, the results, and the conclusions of the study.

Abstract

Bidders in online auctions can choose from among thousands of listed products that vary in quality, quantity and condition. Each listing varies in the amount and quality of information provided by the seller. Prior research suggests that when faced with complex and uncertain situations, individuals tend to use simple heuristics and cues in a bounded rational decision-making process. The current study explores the differences in listings, and the choice and impact of varying information cues on bidding behaviour. Empirical evidence is presented of bidders using the sellers’ minimum (initial) price as a pre-screening signal, and being attracted to auctions with low initial prices while avoiding auctions that have a higher initial price. The research also explores the impact of auction attractiveness on final values, and finds a significant impact of vivid information signals on the number of bidders and the final values of competing auctions.

Keywords: online auctions, eBay, bounded rationality, information effects

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LITERATURE REVIEW

Rationality and bounded rationality

Rationality and irrationality can be viewed as two extremes along a continuum. At one end of the continuum, rationality is descriptive of all those mental processes that consciously strive to master reality. Hence, rational choice implies an avoidance of inappropriate choice, to the extent that individual choices enact their interests (Kalberg 1980; Redmond 2000). Rational choice implies an optimization of utility. This optimization is based on an exhaustive processing of all available information. This information ranges from the utilities of current decisions to those of future actions. Hence, consumers maximize utility by considering current and future consumption, in addition to information provided by advertisements and promotion and any other marketing activities instituted by the seller (Becker 1976, 1996).

In other words, rational choice theory posits an infinite processing capacity of human intelligence (Conlisk 1996). At the other end of the continuum, irrationality implies misappropriated choices based on improper assessments.

With rationality and irrationality at polar opposites, bounded rationality theories recognize the physiological limitations of human cognition (Simon 1990). These cognitive limitations often lead to consumers using different strategies for dealing with information. Even in modestly challenging experiments, systematic reasoning errors and deviations from economic rationality are often evidenced (Conlisk 1996). Psychologists hypothesize that subjects use heuristics or rules of thumb, which fail to accommodate the full logic of a decision. The systematic errors are often referred to as 'biases' or 'heuristics' (Conlisk 1996). For a bounded rational individual these heuristics provide an adequate solution, quickly and cheaply. In other words, there is a trade off between cognitive effort and judgmental accuracy (Pitz and Sachs 1984).

Often evidence suggests that individuals choose among alternatives not by comparing alternatives in all aspects at once, but rather by the heuristic of comparing alternatives one randomly chosen aspect at a time, eliminating alternatives along the way (Tversky 1972). Heuristics are rational in the sense that they appeal to intuition and avoid deliberation cost, but boundedly rational in the sense that they often lead to biased choices. Similar findings by Simon (1955, 1987) suggest that in contrast to standard optimizing theory, when agents are expected to perform exhaustive searches over all possible decisions and then pick the best, agents instead seem to perform limited searches, often accepting the first satisfactory decision. Other concepts such as sub-optimization, wherein decision makers find it difficult to optimize (due to cost or limited ability) and tend to solve a similar approximate optimization problem, show evidence of bounded rationality.

However, most experiments on bounded rationality have come up with contrasting results. In most cases, bounded rational decision makers tend to get increasingly rational and not rely on over simplifying heuristics when they practice and when the experiment provides adequate incentives or punishes the error (Conlisk 1996). These biases are usually attenuated through repeated transactions, stronger incentives, greater initial expertise, better opportunities to learn, deliberation cost and significant stakes (Smith 1989; Smith and Walker 1993). In most cases though, experienced subjects move towards rationality and show a diminishing effect for the use of heuristics and biases.

Auctions and rationality

The consumer auction is a unique form of negotiation where individuals interact to purchase listed products through the strategic disclosure of information. Auctions have been revolutionized by the Internet, which has diminished the spatial, geographical and temporal limitations of traditional auctions. This has spurred the rapid growth of auctions, and its increased prominence and popularity as a viable electronic marketplace. Though various forms of online auctions exist, of particular interest is the consumer auction. The most popular online auction house, eBay hosts over a billion dollars worth of exchanges for thousands of listings. Consumers are attracted to online auctions primarily by the potential of finding bargains, while the network effects of popular auction websites attract sellers.

In most online auctions, the sellers’ listings are organized within categorizes, and vary in information provided by sellers. Sellers balance information with strategy in an attempt to provide adequate product related information, yet maintaining a level of uncertainty about the final expected value. Hence, sellers attempt to maximize their expected valuations by strategic information disclosure. Buyers bid to procure the product at their lowest valuations. The duration of an auction is pre-determined by the seller, and ranges from hours, to days and weeks. Bidders who intend to bid on a product have to screen from among thousands of listings that vary in description, and available information. Upon arriving at a listing or set of listings, the bidders then have to engage in a bidding process, which requires some degree of involvement. Though automatic bidding bots can perform the actual bidding, the prescreening of the listings still needs cognitive effort. Hence the plethora of competing listings and the variance in information levels make online auctions an ideal platform to investigate claims of bounded rationality.

There have been limited explorations into choice behaviour within online auctions. Dholakia and Soltyssinski (2001) suggest that while selecting listings, potential bidders in auctions exhibit ‘herd behavior’ and
use information on the number of bidders who are presently bidding. This non-conscious priming is attributed to the greater variation in product quality, differing seller credibility, and relatively little pre-bid preparation. Hence the existence of current bidders, serves to reduce uncertainty and thereby attract more bidders. However, increased number of bidders in an auction has negative network effects for a new bidder. That is, the higher the number of bidders’ in an auction, the higher the likelihood of competition, and the lower the likelihood of procuring a product at one’s lowest valuation. In other words, the number of bidders in an ongoing auction would signal a higher final price. Hence, it likely that a potential bidder is not pre-screening using the number of bidders alone, but rather in conjunction with other heuristics.

Research on decision-making under ambiguity suggests that consumers look for credible information when making inferences associated with uncertainty (Moon and Tikoo 1997). In such situations, they tend to focus on the limited available information within that context (Jain and Posavac 2001). Empirical evidence suggests that one important heuristic is the seller rating point. The seller rating is a reputation system built on bidder feedback. Resnick and Zecharius (2002) assessed the returns due to eBay’s reputation system, and found that a listing from a seller with positive feedback attracted more bids, than a similar listing from a seller with negative feedback. Interestingly, positive feedback affected prices while negative feedback had no impact on the same. On the other hand, Ba and Pavlou (2002) empirically examined the impact of eBay feedback ratings and found a significant impact of negative ratings against positive feedback ratings. Though oppositional, these findings point to cognitive processing of feedback ratings, and provide evidence of bounded rationality. Vishwanath (2004) extended these findings by comparing the impact of seller ratings across cultures, and found that eBay’s feedback ratings had little impact on cultures high in interpersonal trust, while having a significant impact on bidder participation and final values in a culture low on interpersonal trust.

However, bidders are looking for bargain prices in online auctions. Since bargain hunters by definition seek to procure products at their lowest valuation, a price related signal would then have a prominent impact on choice. All auction listings prominently exhibit the ‘minimum price’ that is set by the seller at the start of the auction. This price could signal the expected valuation of the seller. Low minimum prices could signal the probability of a low final price, and thereby the possibility of a bargain. It could also signal the sellers’ lack of a predefined price, and thereby a willingness to sell at a lower final price. In any case, lower minimum prices signal the probability of a bargain and should attract more bidders to an auction. The more bidders attracted to a low initial value auction, in turn attracts more bidders. Hence the study poses the following hypothesis:

H1: The number of bidders in an online auction would be negatively related to the sellers’ initial price.

In addition to the minimum price, two information formats commonly used by sellers on online auctions are product pictures and reserve prices. These are usually combined with textual descriptions of the product. Of 142 auction websites reviewed by Lucking-Reiley (2000) in the autumn of 1998, 55 sites allowed the use of reserve price and typically 44 of 55 cases indicated the existence of the reserve price on the website next to the auctioned product. To estimate the usage of pictures and reserve prices within the eBay website, a survey of listed auctions for ‘CRT-Monitors’ within the ‘Computer and Peripherals’ category of eBay was conducted over a one-week period of March 2001. This survey netted 2,290 ongoing auction listings, of which close to 37% (857) auctions had some pictorial information (including actual product pictures, and stock pictures), 23% (522) had only a reserve price icon, and 26% (602) auctions had a reserve price and a picture. Lastly, 14% (319) auctions had only textual information (no reserve price, and or pictures). Given the popularity of these two features, the study focuses on their impact on bidders.

Vishwanath and Barnett (in press) empirically examined the effect of the reserve price signal on online auctions. They compared auctions with reserve price icons, against auctions with textual information alone, and concluded that reserve price information affected the number of bidders that the auction attracted, and the resultant bidding strategies adopted by bidders. This provided preliminary evidence of a link between information icons and online auction participation.

In addition to reserve prices, eBay also allows for photographs of auctioned items to be posted along with a description of the product being sold. A standard icon in all the websites flags the existence of a photograph with the item on sale. Standard photos (sizes 3” × 5” or 4” × 6”) are accepted in JPEG or GIF format as attachments to item descriptions. eBay also provides a separate fee-based option of adding up to 4 pictures for each sale item using their hosting service named ‘picture services’. Though there is no direct evidence of the impact of product pictures on auctions, research in advertising has shown that pictures are attention-getting devices (Miniard et al. 1991) that lead to greater message processing and greater message learning by enhancing the memorability of other semantic information (Childers and Houston 1984; Lutz and Lutz 1977). Visual information also affects consumer inferences, such that when pictures and words in an advertisement convey information about different product attributes, the picture claim tends to dominate inference formation (Smith 1992).

Since pictures convey superior visual information, and attract a disproportionate amount of processing (Taylor and Thomson 1982), their impact on reducing bidder
The study intended to collect equal completed auctions for each cell i.e. 50 completed auctions for each information level at which point no further data were collected.

**Procedures**

T tests were conducted on study 1 data to examine the mean difference in number of bidders for auctions with differing initial prices. To compare the effects of varying information levels in study 2, one-way ANOVA was performed on the dependent variable ‘Number of Bidders’. The fixed factor ‘information’ includes pictures, reserve price information, reserve price and pictures, and no information or only textual information. To compare the effects of information on final values a one-way ANOVA was performed on variable ‘Final value’ for varying information levels.

**RESULTS**

**Results of study 1**

In demonstrating ‘herd’ behavior in online auctions, Dholaki and Soltysinski (2001) found a high number of auctions with few bids and a relatively higher number of auctions with multiple bids — which was taken as preliminary evidence of the herd behavior bias. Our preliminary analysis of the data also found a high number of auctions within each category with few bids. Of all completed auctions for Swarovski, 67% (N=268) netted less than 3 bids, while 50% (N=66) of completed auctions for Rolex ladies watches received less than 3 bids. Likewise, 41% (N=79) of completed auctions for Palm VII had less than 3 bids, while 22% (N=196) of those for IBook received less than 3 bids.

Next, an independent sample t-test was conducted on the variable initial value. Table 1 presents the descriptive statistics for number of bidders, and initial value of auctions. The t-test results indicate that all the auctions differ significantly on initial values (p<0.05). Within all product categories, auctions with lower initial values attracted more bidders than comparable auctions with higher initial values, which attracted fewer bidders. Specifically, the t-test results for ladies Rolex watch indicates a significant difference (t=−14.258, p<0.05) in initial values for differing bids. Auctions that received an average of 18 (SD=11.5) bidders had low initial value (M=113.32, SD=153.67). On the other hand, auctions that attracted very few bidders (M=0.667, SD=1.127) had a much higher initial value (M=2398.63, SD=1292.88).

Likewise, the t-test result for the IBook also indicates a significant difference (t=−10.823, p<0.05) in initial value. Auctions that received an average of 17 (SD=8.40) bids had lower initial values (M=337.22,
more ‘deal or bargain seeking’, then the number of bids an auction would signal lesser chances for a bargain final price. In the possibility of that bargain. Then, a higher initial value would signal a higher likelihood of an auction receiving more bids decreases as the initial values of the auction increases. This provides strong support for the hypothesis, suggesting that bidders in auctions use the posted initial value of an auction as a prescreening heuristic.

Results of study 2

Study 2 examined the impact of information levels on the number of bidders and final values of auctions. The ANOVA for the variable ‘number of bidders’ revealed a significant difference, $F(3, 196) = 5.546$, $p < 0.05$, $\eta^2 = 0.070$, for each information level. Table 2 presents the descriptive statistics for ‘number of bidders’. Auctions with pictures received the highest average number of bids, followed by auctions with reserve price and pictures, auctions with only reserve price, and auctions with no information. To explicate the origins of this significant difference, post hoc comparisons using Fisher LSD test was performed. The post hoc comparisons for number of bidders revealed that auctions with pictures attracted a greater average number of bids than auctions with any other information level. Auctions with pictures received a significantly greater average number of bids than auctions with only a reserve price ($M = 4.54$, $SE = 1.93$), and auctions with no information ($M = 7.34$, $SE = 1.93$). Auctions with pictures also received a greater average number of bids than auctions with reserve price and pictures ($M = 1.76$, $SE = 1.93$), however, this difference failed to reach a traditional level of statistical significance ($p = 0.36$). Auctions with reserve price and pictures received a significantly greater average number of bids than auctions with reserve price and pictures ($M = 1.95$, $SE = 1.93$), and auctions with no information ($M = 7.34$, $SE = 1.93$). Auctions with pictures also received a greater average number of bids than auctions with reserve price and pictures ($M = 1.76$, $SE = 1.93$), however, this difference failed to reach a traditional level of statistical significance ($p = 0.36$). Auctions with reserve price and

Table 2. Descriptive statistics for study 2 variable ‘number of bidders’

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<tr>
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<th>With reserve price</th>
<th>Without reserve price</th>
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<tr>
<td>Bidders</td>
<td>M</td>
<td>14.98</td>
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<tr>
<td></td>
<td>SD</td>
<td>8.95</td>
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<td>N</td>
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<tr>
<td>Bids ≥ 4</td>
<td>M</td>
<td>12.20</td>
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<td></td>
<td>SD</td>
<td>8.75</td>
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<td></td>
<td>N</td>
<td>50</td>
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<tr>
<td>Bids ≤ 3</td>
<td>M</td>
<td>11.18</td>
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<tr>
<td></td>
<td>SD</td>
<td>6.78</td>
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<td></td>
<td>N</td>
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Note: Number of bidders represents the unique number of bidders attracted to an eBay auction for each information level.
pictures received a significantly higher number of bids than auctions with no information \((M=5.58, SE=1.93)\), and auctions with only reserve price information \((M=2.78, SE=1.93)\). However, the latter difference was not significant \((p=0.15)\). Lastly, auctions with only reserve price information attracted a higher average number of bids than auctions with no information \((M=2.80, SE=1.93)\), however this difference too failed to reach a traditional level of statistical significance \((p=0.14)\).

The ANOVA for variable 'final values' revealed a significant difference, \(F(3, 191)=4.796, p < 0.05\), \(\eta^2=0.075\). However, since the Levene’s test for equality of variances was significant, \(F(3, 191)=9.799, p < 0.05\), a base 10 log transformation was performed on the dependent variable ‘final value’. The Levene’s test on the transformed variable ‘log of final value’ was not significant, \(F(3, 191)=0.73, p = 0.974\). Table 3 presents the means and standard deviations for variable ‘log of final values’.

Post hoc comparisons using Fisher LSD test revealed that auctions with any information received a significantly higher average final value than a similar auction with no information. Auctions with reserve price and pictures received a significantly higher average final value than auctions with no information \((M=0.466, SE=0.12, p < 0.05)\). Auctions with reserve price and pictures also received a higher final value when compared to auctions with reserve prices \((M=0.25, SE=0.12, p=0.051)\) and pictures \((M=0.11, SE=0.12, p=0.37)\), but these differences were not statistically significant. The difference between auctions with pictures received a significantly higher average final value than auctions with no information \((M=0.35, SE=0.12, p < 0.05)\).

**DISCUSSION**

The findings of the study are noteworthy on two fronts; first they provide a valuable insight into bidder behaviour, and second, they provide effective listing strategies to ensure participation and high auction values.

The findings suggest that bidders in online auctions gravitate to listings with low initial or minimum asking prices. The low initial prices are attractively positioned within most auction websites, and cues potential bidders to the probability of a bargain. Hence, bidders use the initial price of an auction as a prescreening heuristic. The auctions with low initial prices tend to attract more bidders, which in turn attracts even more bidders. This is consistent with the ‘herd behavior’ observed by Dhokalia and Sol tysinski (2001). In conclusion, due to overwhelming nature of online auction choice, value decisions are strategically made by prescreening using simple heuristics or cues.

However, prescreening cues are not limited to only the initial price or the number of bidders. This is consistent with the notion, that in a complex decision scenario, individuals use heuristics to compare chosen aspects by eliminating alternative along the way (Tversky 1972). In addition to low initial prices, other information variables tend to skew bidder choice heavily towards an auction. In particular, information that is more vivid and presents a more concrete view of the product, that is information that aids in value attribution, tends to have a markedly higher impact on choice. Hence in addition to initial price, pictures of products tend to attract the most bidders. This is followed by auctions with reserve price and pictures, only reserve prices, and only textual information (RQ1).

The information levels also impact the final values of auctions (RQ2). These findings are consistent with traditional economic theory linking information to auction values (Milgrom and Weber 1982). Here the findings suggest an interesting dynamic. Auctions with reserve prices and pictures seem to garner the highest final values, followed by auctions with pictures, auctions with only reserve prices, and lastly by auctions with no information. Auctions listed with pictures along with a reserve price (reserve price and pictures) seem to attract relatively fewer bidders but higher final values than an auction with pictorial information alone. A possible explanation could be that the presence of product pictures allows for objective evaluation of the product, but the information that the seller has a reservation price seems to add a dimension of uncertainty, since a winning bid must be in excess of all other bids and meet the sellers reservation price. This appositional affect could result in a valuation gap, leading to an overestimation of the product’s value. This overestimation potentially results in higher final prices for the auction. These findings again reflect traditional economic theory, which terms the overestimation of final values due to competition as the ‘winners curse’ (Capen et al. 1971).

On the other hand, auctions with only reserve price information seem to lack the objective information that pictures provide. The presence of only reserve price

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**Table 3. Descriptive statistics for study 2 variable ‘log of final value’**

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<th>With reserve price</th>
<th>Without reserve price</th>
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<tbody>
<tr>
<td><strong>With pictures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(M)</td>
<td>1.94</td>
<td>1.83</td>
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<tr>
<td>(SD)</td>
<td>0.59</td>
<td>0.68</td>
</tr>
<tr>
<td>(N)</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td><strong>Without pictures</strong></td>
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<td></td>
</tr>
<tr>
<td>(M)</td>
<td>1.69</td>
<td>1.48</td>
</tr>
<tr>
<td>(SD)</td>
<td>0.63</td>
<td>0.63</td>
</tr>
<tr>
<td>(N)</td>
<td>47</td>
<td>48</td>
</tr>
</tbody>
</table>

Note: ‘Log of final values’ represents the transformed base 10 log values of variable ‘final value’.
seems to result in high uncertainty and thereby attract fewer bidders. However, the fact that the seller has a reservation price seems to convey more information than an auction with only textual information. One explanation could be that a seller’s reserve price implies a higher level of quality for the product, thereby resulting in higher final values when compared to auctions with no information. Finally, an auction listing with no information seems to attract the fewest bids and the lowest final value.

With little objective or additional information, auctions with only textual information seem to loose out to auctions with any additional information. With high levels of uncertainty, and fewer bidders attracted to them, these auctions result in the lowest final values.

In conclusion, online auction attractiveness to potential bidders is based on the initial value of the auction, the number of bidders it then attracts, and the extent of vivid information about the product. Auctions with low initial value tend to attract more bidders. When this low initial value is combined with high information levels such as with picture of products, or pictures combined with reserve price notification, the auctions tend to attract more bidders. As more bidders join the auction, there is an escalation of commitment that results in competitive bidding. Here final value is higher when there is reserve price information along with pictures. A seller intending to maximize values is better off with a very low initial price, and more information (reserve price and pictures) rather than less. Though there is a trade off between the numbers of bidders he could potentially attract, the existence of the reserve price along with pictures, guarantees higher final values.

Lastly, the findings of this study are consistent and supported by current research on online auctions. Eaton (2002) found that pictures and positive feedback did signal valuable information to bidders on eBay auctions. Bajari and Hortacsu (2003) found that minimum bids had a significant negative correlation with the number of bidders in an auction. The secret reserve price also correlated negatively with number of bidders, but was not statistically significant. Bapna et al. (2001) similarly found a significant impact of bid increments on the number of active participants in an auction. They found that at lower bid increments the number of active participants in an auction increased, implying that there was more competition and bidding activity. At higher bid increments, many bidders dropped off, implying that the bidders went through fewer rounds of bidding compared to auctions with lower bid increments. Their study points to the impact of price sensitivity and price signals on the number of bidders attracted to an auction. In reconciling their findings with that of the current study, we could conclude that listings from reputed sellers accompanied by pictures and reserve prices, low initial prices, and low minimum bid increments will result in more participation and higher values than any other competing format.

The study suffers from the following limitations. First, due to the variety of listing categories, the study chose only a few categories that differed in the conditions of interest. However, the bidders in each category differ in interest, experience, involvement, and prep bid preparation. All these factors could impact the selection of pre-screening heuristics. Second, the study also assumes that a buyer enters the online auction environment on a given day looking to bid on a particular product. The contrary is often the case, as potential buyers surf the auction websites looking for one or more products. Lastly, there are a number of technology enhancements and service additions on eBay such as ‘buy it now’ options that could readily provide price or value information and reduce uncertainty more effectively.

The effects of such additional variables are probable and future research needs to address their impact on bidding behaviour. Future research also needs to focus on intra-category variations in information effects, especially between products that do not lend themselves to pictorial evaluation such as collectibles and antiques against computers. Researchers could conduct surveys using bidder emails and further understand the motivations of users and the impact of demographics differences on auction participation.

However, the study attempts to recognize the impact of information within online markets such as auctions. Findings from this research provide insight into bounded rational behavior in online auctions, and identify the key prescreening variables that bidders use in their evaluation of products.

References


