Auction or agent (or both)? A study of moderators of the herding bias in digital auctions

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Received 2 April 2001; received in revised form 16 January 2002; accepted 23 January 2002

Abstract

Recent research has shown that buyers in digital auctions are susceptible to the herding bias—gravitation toward listings with existing bids and inconsideration of listings without any bids, manifested in categories of listings that are either coveted or entirely overlooked by buyers. This article investigates two specific types of moderators of herding bias: auction attributes (volume of listing activity, and posting of reservation price) and agent characteristics (seller and bidder experience), and increases our understanding of mechanisms underlying this bias. Practical implications for participants and organizers of digital auctions are discussed, and promising future research opportunities are highlighted. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Auctions; Decision-making biases; Electronic commerce; Consumer behavior

“By three methods we may learn wisdom:
First, by reflection, which is noblest;
Second, by imitation, which is the easiest;
And third, by experience, which is the bitterest”
(Confucius)

1. Introduction

Where many digital business models have been set back by uneven consumer acceptance, slowing growth, and declining stock prices (e.g., Chan, 2001; Sheehan & Hoy, 2000), the digital auction continues to grow in strength, enjoying wide acceptance as a viable business model for conducting electronic commerce (Heun, 2001; Schwartz, 2001). The digital auction refers to a virtual marketplace where geographically dispersed consumers and businesses participate as both buyers and sellers of new and used products and services.

The popularity of digital auctions stems, in part, from their many advantages when compared to traditional auctions. First, both buyers and sellers have more opportunities to obtain the best value in this marketplace. For sellers, there is a much larger pool of potential bidders, less constrained by information,
access or time restrictions. Similarly, for buyers, there is great inter-category assortment and intra-category depth, allowing bidders of all inclinations, from bargain-hunters to collectors to find the object of their search. Second, transaction costs associated with buying and selling here are relatively low for participants, resulting in increased efficiencies (see Wilcox, 2000 for a detailed discussion). Third, the wide audience and perpetual progress of digital auctions allow many sellers to engage in on-going sales on a flexible basis. Such steady sales are less feasible for agents in traditional auctions, which convene infrequently. Fourth, many sellers use auctions to generate advertising in an inexpensive fashion as well. Finally, the digital auction model benefits from positive network externalities in that its aggregate value increases as new users, buyers or sellers, join the marketspace (Shapiro & Varian, 1999). All of these attributes have elicited comparisons to ideal markets: “(they)... appear to be a close approximation of an economist’s idealization of a frictionless, competitive market” (Bajari & Hortacsu, 2001, p. 1).

In spite of this prevailing enthusiasm, recent research has shown that just as in traditional arenas of exchange, buyers in digital auctions are also susceptible to decision-making foibles (Dholakia, 2002; Dholakia & Soltysinski, 2001). Dholakia and Soltysinski (2001) provided evidence of the herding bias—many buyers tended to bid for listings with existing bids, ignoring comparable or more attractive unbid-for available listings within the same category. The herding bias was reflected in a significant proportion of coveted listings, attracting many bidders, and the corresponding overlooked listings, that were essentially identical to, and in many cases, more desirable than, one or more corresponding coveted listings, but attracting no bidders at all. For the buyer, susceptibility to the herding bias implies that he/she may end up paying a higher price or winning a less favorable listing than necessary. Similarly, because of this bias, the possibility that a listing, competitive in all respects, may remain unnoticed and fail to find buyers while some other inferior listing is furiously bid to a high price—arises for the seller. More generally, herding bias occurrence implies that contrary to conventional wisdom, neither every buyer nor every seller receives the best value from participating in digital auctions.

Dholakia and Soltysinski (2001) also showed that the herding bias is attenuated with increasing listing price but increases as the listing quality becomes difficult to evaluate for buyers. In this analysis, buyers were less likely to overlook comparable listings as the price increased, but were more likely to do so, and gravitate toward coveted listings, when the listing’s quality became difficult to evaluate. Our goal in the present research is to further analyze the data set initially reported in the Dholakia and Soltysinski article, and build on their exploratory research through understanding the role played by two important types of factors on the extent and nature of herding bias occurrence: auction attributes and agent experience. In a sense, the present article represents progress from the first generation of the research issue (i.e., showing the existence of the bias) to the second generation (i.e., developing an understanding of the mechanisms and boundary conditions underlying the bias), as well as understanding the implications of this bias for participants and organizers.

In considering auction attributes, we hypothesize that the degree of bias occurrence is a quadratic function of the category-level listing volume. We also posit that posting a reservation price reduces the possibility that the listing will be overlooked, and increases its chances of being coveted. Next, we examine the influence of seller and bidder experience on the extent of herding bias occurrence. We expect that increasing experience should mitigate bias susceptibility for both agents in the transaction. Taken together, these findings increase our understanding of the social and psychological mechanisms underlying herding bias in digital auctions. Just as important, this research provides guidance in specific terms to digital auction participants and organizers.

The rest of this article is organized as follows. In the next section, we begin with an overview of what is known about the herding bias. This is followed by the research hypotheses, and the results of the empirical study utilizing data from a large number of digital auctions, from several different categories. We conclude with a discussion of important theoretical and practical insights stemming from this work, along with some opportunities for future research in this area.
2. Research overview

2.1. Psychological processes of bidders in digital auctions

Buyer behavior in digital auctions may be construed as hierarchical—that is, progressing from the listing category, to a consideration set, and then to individual listings (Dholakia & Bagozzi, 2001), and constructive—in that choices are often determined during online navigation, rather than formed beforehand (e.g., West, Brown, & Hoch, 1996). Moreover, because of the large number of listings in most categories, the middle-level prescreening task, that is, narrowing down a small subset of listings for detailed consideration, is likely to gain greater importance for the individual bidder (Beach, 1993). In explicating mechanisms underlying the prescreening process, behavioral decision research has shown that individuals typically use a simple and quickly executable heuristic to narrow down the unwieldy choice set to a manageable few (Beach, 1993). Such a rejection heuristic, which eliminates the majority of available options, is typically formed using information readily available to the decision maker. In digital auctions, decision makers have few information elements to make use of during prescreening. These typically include title description of the listing, its ending time, current bid price or posted minimum price (if available), and the number of existing bids. While all these elements are more-or-less equally accessible in the information environment during the prescreening process, which of them is used in the heuristic will depend on their perceived diagnostic value.

2.2. Informational social influence

In studying social environments such as digital auctions, psychologists have found that the observable behavior of others exerts a strong influence on individuals. Others’ observed behavior may guide goal-directed behavior by benefiting two salient types of motives of the decision maker: first, to be accurate and make “good” decisions, called informational motives, and second, a concern for other people and the outcomes derived from them, called social motives (Cialdini & Trost, 1998; Pool, 1999). When bidding in a digital auction, others’ preceding behavior may provide valuable information, and may be perceived as having greater credibility than seller-originating content such as descriptions or pictures, since it arises from presumably credible sources (after all, what ulterior motive could another bidder have?). It may therefore signal less uncertain and more positive outcomes to many buyers. The process of self-categorization—social identification with other bidders—may further increase the influence of this cue. It is useful to note that this perspective is consistent with both common values and affiliated values auction models in the economics literature, which posit that the individual bidder stands to gain significantly from any information regarding the bidding behavior of others (McAfee & McMillan, 1987; Milgrom & Weber, 1982).

2.3. Informational cascades

The economics literature on informational cascades (cf., Bikhchandani, Hirschleifer, & Welch, 1992) further elaborates on the importance of others’ behavior in the decision maker’s own actions. An informational cascade occurs when a decision maker uses the behavior of preceding others as a signal conveying its efficacy in goal attainment, even disregarding other information that he/she may have (Bikhchandani et al., 1992). Such imitative behavior occurs, in part, because of the notion that previous consensus behavior may embed information not yet available to oneself (i.e., “they must all know something that I don’t”; e.g., Prendergast & Stole, 1996). Further, information cascades are more likely to occur in environments that are uncertain, those where individuals have more-or-less similar preferences to at least some others, are able to express their preferences sequentially in a meaningful manner, and also in cases where the quality of outcomes for any one participant is relatively difficult to ascertain (Bikhchandani et al., 1992)—all of which characteristics apply to digital auctions.

To summarize, we posit that many bidders in digital auctions may use the existing number of bids for the listing in their prescreening heuristic for three reasons. First, this information is readily accessible as bidders engage in their search and prescreen alterna-
tives, within the digital auction. Second, it provides valuable information, signaling the listing’s quality, the seller’s trustworthiness, or both. Finally, it represents a verbalizable and plausible reason for prescreening—which other consumer research has shown to be influential in the choice process of buyers (e.g., Simonson & Nowlis, 2000).

2.4. Manifestation of the herding bias in digital auctions

When many bidders in digital auctions use other bidders’ behavior as a cue to infer value and to prescreen listings, the herding bias may result, manifested by two distinct groups of listings. Those in the first category receive a large number of bids, and rise up to a high final price, even though they may be no better than (or indeed, may even be inferior to) other unbid-for available listings, resulting in unexpected success for the seller but a poor value for the winning bidder. Such listings have been called as “coveted” by Dholakia and Soltysinski (2001), and accentuate the “winner’s curse” (e.g., Bajari & Hortacsu, 2001). On the other hand, listings in the second category remain “overlooked” in the sense that such listings may be equivalent or even superior to coveted listings but fail to receive any bids. The extent of herding bias is reflected in the likelihood of a listing remaining overlooked or becoming coveted in digital auctions.

3. Research hypotheses

Two important categories of factors are likely to influence the degree to which the herding bias occurs in digital auctions: auction attributes (volume of available listings, and posted reservation price), and agent characteristics (buyer and seller experience). These factors are chosen for study because they are observable by all auction participants, provide interesting insights into the mechanisms underlying herding bias, and are of practical relevance to buyers and sellers. Other factors such as disposition of participants may also play a role, but are not considered here. Specific research hypotheses pertaining to each of these factors are developed in this section.

3.1. Herding bias as a quadratic function of category-level listing volume

While popular digital auctions add millions of new listings on a daily basis, there is considerable variation in volume across categories. In a recent exhaustive survey of digital auctions, Lucking-Reiley (2000) found that more than 75% of all listings on eBay pertained only to collectibles. In contrast, very few listings were available for movie tickets or plumbing services. Listing volume is a barometer of the category’s popularity in that the variation in volume across categories not only reflects, but also shapes, buyer and seller interest and participation in these categories. We expect listing volume to play an important role in determining the extent of the herding bias, as follows.

When compared to traditional retail settings, digital auctions are characterized by a much greater variation in available choices. Even when searching for a specific brand, the buyer may encounter considerable variation on different fronts: the country of origin, the extent of description, the number and quality of pictures used, whether the product is new or used, whether other accessories or services are bundled with it, its asking price, etc. Moreover, in most cases, the seller is unknown to the buyer. These characteristics all decrease the comparability of available listings.

At very low listing volumes, we expect such uncertainty to be of great import to buyers. Under such ambiguous circumstances, buyers may get fewer opportunities to learn about prevailing prices or attributes within the digital auction, to get acquainted with specific sellers, or to develop accurate expectations (Johnson, Anderson, & Fornell, 1995; Muthukrishnan, 1995). Further, because of fewer alternatives, the variation between existing listings may actually be perceptually accentuated, making comparisons even more difficult. In such cases, research has shown that decision makers tend to selectively focus on those attributes which are the most comparable across alternatives (Muthukrishnan, 1995; Slovic & MacPhillamy, 1974). The number of existing bids represents this readily available, comparable attribute between the sparse listings in such categories, and is therefore likely to be quite influential. A similar phenomenon may be observed in the choice of patrons at two adjacent restaurants, manifested in one having long waits and
teeming crowds, while the other remains nearly empty. Here, the crowd itself may draw newly arriving patrons to the already crowded restaurant.\footnote{We thank a reviewer for making this insightful point and for suggesting this analogy.}

Moreover, research on network externalities suggests that networks failing to reach a critical size diminish in popularity, attracting fewer new members, and losing existing ones (Shapiro & Varian, 1999). Such is likely to be the case for low volume categories.

In these conditions, fewer bidders in the aggregate are likely to participate and bid for items—resulting in fewer coveted listings, but many overlooked ones. To summarize, when listing volume is low, we expect listings to have a low likelihood of being coveted, but a high likelihood of being overlooked.

As listing volume increases, individual buyers have more options to choose and learn from. The buyer now has less need to rely on others’ behavior as a means of reducing uncertainty. The greater listing activity also harnesses the “virtuous cycle” of networks, attracting more bidders and more aggregate bids for the listed items. In general, the likelihood of being coveted should increase while the likelihood of being overlooked decreases. But at the same time, higher volume implies that the bidder has to spend more time when deciding to consider all posted listings. With heavier volume then, the need for, and the importance of the prescreening heuristic also increases. For heavy volumes, the buyer must prescreen alternatives—it will be virtually impossible to consider all available listings in-depth—and may use the existing number of bids to do so. At the same time, competition among listings for the interested bidders also increases with increasing volume. As a result, while the likelihood of being overlooked rises again, the chances of being coveted should diminish at very high listing volumes.

To summarize, where we expect reliance on others’ behavior on account of decision ambiguity to be high at very low listing volumes, and to decrease with heavier volume, we expect reliance on others’ behavior as a prescreening heuristic to increase with volume. In either case, the resulting consequence will be a tendency to gravitate toward listings with existing bids, accentuating the likelihood of being overlooked. Consequently, we expect the relationship between listing volume and likelihood of being overlooked, to be \textit{U}-shaped (see Fig. 1). In contrast, mechanisms of network effects will influence the incidence of coveted listings as volume increases. At low levels, fewer aggregate bidders will result in less likelihood of being coveted. With increasing volume, the likelihood of being coveted will increase as more bidders get interested, participate in, and bid for listings. But at very heavy volumes, the greater competition between listings and the many available choices will ensure that the likelihood of being coveted is reduced again. The relationship between listing volume and likelihood of being coveted is therefore posited to be \textit{inverted U}-shaped. These relationships are shown in Fig. 1, and the discussion is summarized in the following research hypotheses:

\textbf{Hypothesis 1}. In digital auctions, the likelihood of being overlooked is \textit{low} for medium levels, compared to low or high levels of listing volume.

\textbf{Hypothesis 2}. In digital auctions, the likelihood of being coveted is \textit{high} for medium levels, compared to low or high levels of listing volume.

It is important to note that in this research, listing volume is conceptualized in relative terms intra-category, but in absolute terms across categories. In other words, a “low” volume signifies the same small number of postings, irrespective of category, and so forth.

3.2. Role of reservation price

In digital auctions, the seller can choose whether to post a reservation price, the minimum price below which he/she refuses to sell. Its role can be better understood by considering the informational environment of digital auctions, which is characterized by \textit{asymmetry} between buyers and sellers arising from the different uncertainties discussed before. Existing research shows that reservation price plays an influential role in information asymmetric environments by indicating both a commitment on the seller’s part (to suffer negative consequences), and a signal of the offering’s quality, reducing the bidder’s risk. More importantly, in the context of information available to the bidder, reservation price is likely to be both readily accessible and comparable across alternatives. We
expect it to act as a potent diagnostic signal, supplanting the value of number of existing bids, and to be used instead, by many bidders, in the prescreening heuristic. It may also serve as a surrogate first-bid, enabling bidders to cross the Rubicon of hesitation that causes many listings to remain overlooked. Consistent with this argument, Bajari and Hortacşu (2001) found the presence of a reservation price to be the single-most important determinant of the buyer’s decision to bid for a listing. Based on this reasoning, the following hypothesis can be stated:

**Hypothesis 3.** For listings in digital auctions, the presence of a reservation price decreases the likelihood of being overlooked.

Further, research in economics analyzing equilibria under different auction rules has established that if the seller posts an observable reservation price, the average final sale price tends to increase, relative to the case where a reservation price is not posted (e.g., Elyakime, Laffont, Loisel, & Vuong, 1994; Milgrom & Weber, 1982). In a representative study, Elyakime et al. (1994) show that providing a reservation price always yields the seller higher revenue than when it is not used. McAfee and McMillan (1987) summarize the value of the reservation price as follows: “(for the seller) any one of the English, Dutch, first-price sealed-bid, and second-price sealed-bid auctions is the optimal selling mechanism provided it is supplemented by the optimally set reservation price” (p. 714, emphasis added). Based on the assumption that the seller posts a reservation price “optimally” that is, reflecting the value of the listing rather than unreasonably high (Klemperer, 1999), the initial gravitation toward listings with a reservation price is more likely to be augmented by escalation mechanisms, resulting in their eventually being coveted.

The literature on merchant-supplied reference prices (e.g., Lichtenstein & Bearden, 1989) supports this reasoning as well. This research suggests that reference prices supplied by sellers alone, as well as in conjunction with other contextual variables, increase the consumers’ perceptions of the value of the prod-
uct. In a sense, a reservation price in a digital auction is close to a merchant-supplied reference price in other settings, and is therefore likely to contribute to the value perceptions of bidders. Based on this discussion, the following hypothesis can be stated:

**Hypothesis 4.** For listings in digital auctions, the presence of a reservation price increases the likelihood of being coveted.

### 3.3. Role of seller experience

The herding bias may be beneficial or detrimental to sellers depending on whether their listings become coveted or get overlooked. In either case, however, because buyers initiate and engage in bidding behaviors that cause the bias, it represents a source of uncontrollable outcome for sellers. From the seller’s perspective, avoidance of the negative consequence of the herding bias implies a specific objective: to receive at least one bid, to cross over the Rubicon of remaining overlooked.

As discussed before, posting a reservation price may accomplish this. In addition, sellers have many marketing tools available to them. They can post alluring pictures or videos, use an attention-catching title description in the category index, or offer free shipping, multiple-purchase discounts, and other promotional incentives. We expect that experienced sellers learn to use these tools judiciously and proficiently, resulting in their listings receiving greater and more favorable attention from buyers relative to novice sellers.

Moreover, as the same seller lists products over a period of time, we expect that he/she becomes known to at least some regular buyers, and more trusted by them. Such buyers will therefore be more likely to bid for listings of this known seller, with lesser emphasis on listing attributes. On the basis of this discussion, we expect that listings of experienced sellers will be less likely to be overlooked. This reasoning is summarized in the following research hypothesis:

**Hypothesis 5.** For sellers, the likelihood of being overlooked decreases with increasing selling experience in digital auctions.

From a theoretical standpoint, it is important to note that sellers have little control once the auction gets underway. The bidding decisions and actions of buyers then drive and determine the listing’s success. We therefore make no specific predictions regarding the direct relationship between selling experience and the listing’s likelihood of being coveted, in digital auctions.

### 3.4. Role of bidder experience: outsmarting the herd

In the auctions literature, experience is viewed as important in determining bidding behaviors as well. For instance, when examining valuation auctions in laboratory settings, economists have found that novice bidders initially pay a price premium, but this declines significantly as they gain bidding experience (Hayes, Shogren, Shin, & Kliebenstein, 1995). This initial price premium is thought to arise from the novelty of the auction experience as well as the offerings bid on. Both these sources make novice bidders more willing to pay an initial price premium, almost as tuition fees for learning how the auction works (Shogren, List, & Hayes, 2000). With experience, their preferences become more stable and they become less amenable to paying price premia.

In the literature on informational cascades too, economists have found that the incentive to herd declines as the decision maker becomes more experienced and certain of his/her ability (e.g., Scharfstein & Stein, 1990). A similar argument can be advanced for the individual bidder in digital auctions. The perceived benefits from emulating others or winning popular, coveted auctions are likely to be more important for the novice bidder. Participating in auctions with existing bids may have significant educational value, enabling the bidder to become acquainted, not only with the procedures entailed in placing and revising bids, but also in learning successful bidding strategies from more experienced bidders. As the bidder gains more experience with, and confidence from, bidding and winning auctions, the efficacy of others’ behavior in guiding one’s own choice is likely to decrease. This points to greater participation in, and winning of coveted digital auctions by novice bidders, and vice versa, and is framed by the following research hypothesis:

**Hypothesis 6.** For bidders, the likelihood of winning coveted auctions decreases with increasing buying experience in digital auctions.
Note that we make no specific predictions about how the individual bidder’s experience might influence the listing’s likelihood of being overlooked. However, for any bidder, the herding bias has two implications. On the one hand, susceptibility to the bias may result in one receiving a poor value from winning a coveted auction. In stark contrast, if a buyer swims against the current, ignores others’ behavior, and seeks out overlooked listings to bid on, a superior value may be obtained from the auction on account of others’ biased behavior. We expect that while novices may be more likely to follow the first route, seasoned bidders may be more likely to benefit from the second route.

Existing research in consumer psychology provides insights in this regard. In examining consumer decisions, Johnson and Lehmann (1997) found that with increasing experience, the number of alternatives in consumers’ consideration sets also increases. In the auction context, this result suggests that experienced bidders may consider more of the available listings, and consequently be more likely to come across listings that have not received any bids. Johnson and Lehmann also examined the role of consumer experience on the prototypicality of consideration sets, which they defined as the extent to which a particular category member is a better exemplar of that category. They found that, compared to novices, experienced consumers were likely to have consideration sets that were less prototypical, suggesting that they cast a wider net during the decision process. Other research has shown that with increasing experience, consumers understand the product domain better, and define it more broadly. As a result, they are able to use more and better suited attributes when making decisions (Alba & Hutchinson, 1987). These findings all suggest that not only do experienced buyers have a lesser need to rely on others’ bidding behavior, but they are also more likely to actively seek out overlooked listings and bid first for them, hoping to get a better value. Based on this discussion, the following hypothesis can be stated:

Hypothesis 7. For buyers, the likelihood of bidding first for zero-bid listings increases with increasing buying experience in digital auctions.

4. Methodology

To test the research hypotheses, bidding data were collected from eBay. eBay was chosen since it is the largest digital auction as of this writing, facilitating the buying and selling of items in more than 4000 different categories, with 4 million new daily auctions, and over 10 million registered users. A recent exhaustive survey of digital auctions found that over 75% of all transactions through digital auctions were conducted on eBay (Lucking-Reiley, 2000). Further, data from eBay have been used in recent digital auction research (e.g., Bajari & Hortaçsu, 2000; Wilcox, 2000).

Data on all completed auctions within a 3-week period in the summer of 2000 were collected for four listing categories: portable CD player, Italian silk tie, Mexican pottery, and Playstation console. The four categories were chosen to ensure a wide variety with regard to type of offering and listing activity. Preliminary research had indicated that bidders interested in these products begin their search by entering these categories as search terms. These categories therefore correspond to what cognitive psychologists have called “basic categories” (Rosch, Mervis, Gray, Johnson, & Boyer-Braem, 1976), that is, they possess the highest category cue validity and form the basis of “comparable” decision making—consumers make the decision to buy within this category first, followed by attribute-based evaluation of specific alternatives within this category.

Data on a total of 2053 auction listings were collected (Portable CD player = 753 listings, Playstation console = 221 listings, Italian silk tie = 270 listings, Mexican pottery = 809 listings). The information collected included the final (or in the case of zero bids, the listed) price, total number of bids, starting and ending dates, a detailed description, whether there was a reservation price, the number of unique bidders and the number of available listings during the time the listing was posted. In addition, experience ratings of both the seller and the winning bidder as measured by the number of previous auctions in which he/she had participated and either successfully sold the item (for the seller) or won the item (for the buyer), were also collected for each listing. Experience ratings of agents in eBay auctions are directly observable for all participants.

Hypothesis 7. For buyers, the likelihood of bidding first for zero-bid listings increases with increasing buying experience in digital auctions.

Hypotheses 6 and 7 develop an understanding of how bidders may strive to outsmart the herd in digital auctions.
All listings were coded as overlooked, coveted, or neither, by two different judges using qualitative research principles (Strauss & Corbin, 1990). An overlooked listing was defined as one that (1) received no bids, (2) was judged as identical or superior to at least one listing that received one or more bids within the previous or subsequent 3-day period, and (3) had a lower or equivalent list price than the bid-receiving listing. Similarly, a coveted listing was judged as one that was (1) identical or inferior to one or more overlooked listings identified in the preceding or subsequent 3-day period, (2) had more than one bidder, and (3) with a higher final price than the corresponding overlooked listing.

A 3-day window of time was used in classifying listings as coveted or overlooked based on the reasoning that buyers would engage in at least some search during the pre-screening process. This assumption is also consistent with the exploratory mind-set of digital auction buyers. Additionally, it represents less than half of the 1 week for which most digital auctions run. Admittedly, a smaller window of opportunity would result in a more stringent definition of overlooked and coveted listings, and vice versa. Further, since only completed auctions were included in the analysis, temporality of corresponding overlooked and coveted listings was not considered explicitly in the classification. In other words, an overlooked listing could have been posted before or after the corresponding coveted listing. This assumption is reasonable for digital auctions because of the asynchronicity of the exchange mechanism: bidders typically have several days to consider, bid, and follow-up on any particular listing, and typically engage in a temporally drawn bidding strategy, rather than visiting the auction, and bidding just once, for any listing (Dholakia & Bagozzi, 2001). It is also important to note that the two categories of overlooked and coveted listings are characterized by a many-many correspondence between individual category members such that one member of the coveted category may correspond to one or more members of the overlooked category, and vice versa.

The judges were provided with a detailed list of attributes to consider, when coding listings as overlooked, coveted, or neither. These included brand name, make and model (for Playstation console and portable CD player), features (e.g., anti-shock protection, dynamic boost system for portable CD player; glazed, hand-painted, signed, etc. for Mexican pottery), type, size and number (for Mexican pottery), condition (new or used), color, etc. Some additional details of the coding scheme are provided in Appendix A. In general, judges coded a listing as overlooked as soon as they found one inferior or equivalent listing with multiple bids, and coveted when they found one corresponding superior or equivalent listing without any bids, during the specified time-frame. This simplified the coding task somewhat, and made it manageable.

However, it is important to point out that neither judge had any special expertise with regard to any of the four categories, but solely used the objective attributes provided, when classifying listings. It is also important to acknowledge that our emphasis on objective criteria for comparison may have missed some idiosyncratic qualities of particular listings resulting in their non-classification. As a result, we expect such oversights to have resulted in a conservative set of classified listings.

The two judges made a total of 1463 decisions when judging listings as overlooked or coveted. Of these, there were a total of 169 (or 11.6%) disagreements, each of which was resolved by discussion, when finalizing the coding scheme. In general, the coding scheme was characterized by a satisfactory degree of stability and robustness. For the entire sample of auction listings, across the four categories, 21.8% of the listings were classified as overlooked (Playstation = 4.5%, CD Player = 10.5%, Mexican pottery = 30.8%, and Italian tie = 40.7%), while 39.4% of the listings were coded as coveted (Playstation = 40.7%, CD Player = 64.5%, Mexican pottery = 24.7%, and Italian tie = 11.9%). Coveted listings received an average of 11.3 bids from 7.9 unique bidders. The final average bid price of coveted listings was US$94.50. In contrast, overlooked listings had an average listing price of US$32.40.

5. Results

To test the research hypotheses, two logistic regression models were built, one for testing all the research

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2 The condition of multiple bidders explicitly takes into account the use of existing bids as a cue to infer the listing’s value.
hypotheses pertaining to the likelihood of being overlooked (H1, H3 and H5), and a second model with the likelihood of being coveted (H2, H4 and H6) as the dependent variable. The following models were estimated:

\[
\text{Pr(overlooked)} = \alpha_1 + \beta_1 (\text{Numlist}) + \beta_2 (\text{Numlist})^2 + \beta_3 (\text{Reserpric}) + \beta_4 (\text{Sellerexp}) + \beta_5 (\text{Numlist} \times \text{Sellerexp}) + \beta_6 (\text{Reserpric} \times \text{Sellerexp})
\]  

(Model 1)

\[
\text{Pr(coveted)} = \alpha_2 + \gamma_1 (\text{Numlist}) + \gamma_2 (\text{Numlist})^2 + \gamma_3 (\text{Reserpric}) + \gamma_4 (\text{Bidderexp}) + \gamma_5 (\text{Numlist} \times \text{Bidderexp}) + \gamma_6 (\text{Reserpric} \times \text{Bidderexp}) + \gamma_7 (\text{Sellerexp})
\]  

(Model 2)

Pr(overlooked): probability that a listing is overlooked; Numlist: number of listings at the category level; Reserpric: whether the listing had a reservation price (0 ⇒ no, 1 ⇒ yes); Sellerexp: experience rating of the seller.

Model 1 provides a test of Hypotheses 1, 3, and 5. In addition, to determine whether seller experience interacts with either of the auction characteristics, interaction terms were also included in the model.

Pr(coveted): probability that a listing is coveted; Numlist: number of listings at the category level; Reserpric: whether the listing had a reservation price (0 ⇒ no, 1 ⇒ yes); Bidderexp: experience rating of the winning bidder; Sellerexp: experience rating of the seller.

Model 2 provides a test of Hypotheses 2, 4, and 6. In addition, to determine whether the bidder’s experience interacts with either of the auction characteristics, interaction terms were also included in the model. We also included seller experience as a control variable in Model 2, although we had no specific hypothesis regarding this variable, for coveted listings. A summary of the research hypotheses and the results are provided in Tables 1 and 2 below.

As can be seen from Tables 1 and 2, all of the coefficients from both Models 1 and 2 are statistically significant and in the hypothesized directions, respectively. The analysis generally supports the research hypotheses. Our first hypothesis stated that the likelihood of being overlooked would be higher at both, low and high volumes of listing activity, relative to the medium volume. Supporting this, the coefficient of the linear “Numlist” coefficient is negative and statistically significant (\(\beta_1 = -0.03, p < 0.01\)) while the quadratic coefficient is positive and significant (\(\beta_2 = 0.0005, p < 0.001\)) in Model 1. Hypothesis 1 is supported, suggesting that both low and high volume categories increase a listing’s likelihood of being overlooked by bidders. To verify this result, we classified daily listing activity into three levels: high (top third, 41 or more), medium (middle third, 26–40), and low (bottom third, 25 or less), and computed the quadratic trend for proportion of overlooked listings using planned contrasts. The percentages of overlooked listings in the high, medium, and low categories were 24%, 19.5%, and 27.6%, respectively. Results of planned contrasts \(\{M_{\text{high}} - M_{\text{medium}}, (M_{\text{medium}} - M_{\text{low}})\} \) were both significant, 0.04 \((p < 0.05)\) and 0.08 \((p < 0.01)\), respec-

---

### Table 1
Results of Model 1

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Model estimate</th>
<th>Wald statistic</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Effect of listing activity on being overlooked</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\beta_1 &lt; 0)</td>
<td>(\beta_1 = -0.03)</td>
<td>6.88</td>
<td>(p &lt; 0.01)</td>
</tr>
<tr>
<td>(\beta_2 &gt; 0)</td>
<td>(\beta_2 = 0.0005)</td>
<td>10.40</td>
<td>(p &lt; 0.01)</td>
</tr>
<tr>
<td>H3: Effect of reservation price on being overlooked</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\beta_3 &lt; 0)</td>
<td>(\beta_3 = -0.71)</td>
<td>21.11</td>
<td>(p &lt; 0.01)</td>
</tr>
<tr>
<td>H5: Effect of seller experience on being overlooked</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\beta_4 &lt; 0)</td>
<td>(\beta_4 = -0.0004)</td>
<td>5.20</td>
<td>(p &lt; 0.05)</td>
</tr>
<tr>
<td>Interaction of listing volume and seller experience</td>
<td>(\beta_5 = -6.03e^{-6})</td>
<td>1.94</td>
<td>(p &gt; 0.15)</td>
</tr>
<tr>
<td>Interaction of reservation price and seller experience</td>
<td>(\beta_6 = -2.6e^{-5})</td>
<td>0.008</td>
<td>(p &gt; 0.90)</td>
</tr>
</tbody>
</table>
Interaction of reservation price and buyer experience

H4: Effect of reservation price on being coveted

Seller experience (control variable)

Interaction of listing volume and buyer experience

Results of Model 2

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Model estimate</th>
<th>Wald statistic</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>H2: Effect of listing activity on being coveted</td>
<td>$\gamma_1 = 0.085$</td>
<td>45.03</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>$\gamma_2 &lt; 0$</td>
<td>$\gamma_2 = -0.001$</td>
<td>38.44</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>H4: Effect of reservation price on being coveted</td>
<td>$\gamma_3 = 0.269$</td>
<td>8.37</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>H6: Effect of buyer experience on being coveted</td>
<td>$\gamma_4 = -0.003$</td>
<td>6.47</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>Interaction of listing volume and buyer experience</td>
<td>$\gamma_5 = 7.83 \times 10^{-5}$</td>
<td>5.96</td>
<td>$p &lt; 0.05$</td>
</tr>
<tr>
<td>Interaction of reservation price and buyer experience</td>
<td>$\gamma_6 = 0.002$</td>
<td>1.96</td>
<td>$p &lt; 0.10$</td>
</tr>
<tr>
<td>Seller experience (control variable)</td>
<td>$\gamma_7 = 2.4 \times 10^{-4}$</td>
<td>8.32</td>
<td>$p &lt; 0.05$</td>
</tr>
</tbody>
</table>

Comparatively, providing corroborative support to the quadratic trend in Hypothesis 1.

Hypothesis 2 posited that the opposite would be the case for coveted listings. Listings would be less likely to be coveted at both, low and high volumes relative to medium levels. This is indeed borne out by Model 2 results. Here, the linear “Numlist” coefficient is positive and statistically significant ($\gamma_1 = 0.085, p < 0.001$) while the quadratic coefficient is negative and statistically significant ($\gamma_2 = -0.001, p < 0.001$). Hypothesis 2 receives statistical support. The quadratic trend was confirmed as before using the categorized listing activity as the independent levels, and conducting planned contrasts. The percentages of coveted listings in the high, medium, and low categories were 29.9%, 48%, and 29.3%, respectively. Results of planned contrasts \{(M_{high} - M_{medium}), (M_{medium} - M_{low})\} were both significant, −0.18 ($p < 0.001$) and 0.19 ($p < 0.001$), respectively, supporting Hypothesis 2.

Hypothesis 3 posited that when a reservation price is posted, listings should be less likely to be overlooked. A significant negative $\beta_3$ coefficient in Model 1 ($\beta_3 = -0.71, p < 0.001$) provides statistical support to this hypothesis. Listings with a reservation price were significantly less likely to be overlooked compared to listings without one [$M_{\text{reserve}} = 66.3\%$ vs. $M_{\text{noreserve}} = 36\%, F(1, 2051) = 18.8, p < 0.001$], supporting Hypothesis 4.

Hypothesis 5 suggested that sellers should be less likely to have their listings overlooked with increasing experience. A test of this hypothesis is provided by the $\beta_4$ coefficient in Model 1. From Table 1, as hypothesized, $\beta_4 = -0.0004, p < 0.05$, statistically supporting Hypothesis 5. Sellers do appear to learn to minimize the negative consequences of the herding bias as they gain experience with selling in digital auctions. To further corroborate this result, we considered the listings of the most experienced (top 10%) and the least experienced (bottom 10%) sellers. Where 14.9% of the listings of the most experienced sellers were overlooked, 30.2% of the listings of the least experienced sellers remained overlooked, the difference being statistically significant [$F(1, 427) = 2.5, p < 0.01$], and supporting Hypothesis 5.

Hypothesis 6 posited that buyers should be less susceptible to the negative consequences of the herding bias, that is, less likely to win coveted auctions, as they gain more bidding experience. This hypothesis is tested by the $\gamma_4$ coefficient in Model 2. As hypothesized, it is found to be negative and statistically significant ($\gamma_4 = -0.003, p < 0.001$), suggesting that buyers become less likely to win coveted listings with increasing experience. In this case too, we compared the most (top 10%) and least (bottom 10%) experienced buyers. Where 47.5% of listings purchased by the most experienced buyers were coveted, 59.7% of those purchased by the least experienced buyers were so, a statistically significant difference [$F(1, 432) = 5.061, p < 0.05$]. Interestingly, the most experienced sellers purchased a greater proportion of Playstations...
and CD players than average, categories high in coveted listings, but still had a lesser proportion of coveted listings than the least experienced buyers.

As noted before, interaction terms were also included in both models to examine the possibility that agent experience interacts with auction attributes. Results showed that in Model 1, neither the interaction of seller experience with listing volume ($\beta_5 = -6.03e^{-6}$, ns) nor with reservation price ($\beta_6 = -2.6e^{-5}$, ns) was significant (see Table 1). This suggests that more experienced sellers do not appear to systematically take advantage of either auction characteristic to minimize the danger of being overlooked. In Model 2 also, while the interaction of bidder experience with listing volume ($\gamma_5 = 7.8e^{-5}$, $p<0.05$) was significant, that of reservation price with bidder experience ($\gamma_6 = 0.002$, ns), was not (see Table 2). Interestingly, the seller experience included as a control was found to be significant as well, suggesting that listings of sellers may be more likely to become coveted with experience.

In addition, in response to a reviewer’s suggestion, to consider the role of second-and higher order interactions among the independent variables in more depth, we conducted additional analyses. Both the buyer and the seller experience variables were dichotomized by a median-split, and the listing volume variable was tri-partitioned into high, medium, and low activity levels. Separate categorical independent-variable logistic regression models were then built, corresponding to the two models described above with the overlooked or coveted listings indicator as the dependent variable, and the appropriate two- and three-level variables as the independent factors, along with all higher order interactions. In the overlooked listing model, all three main effects remained significant. While some two-way interactions were also significant in this model, the three-way interaction was not. In the coveted listing model, while the main effect of listing volume was significant, that of buyer’s experience became marginally significant ($p<0.1$), while the main effect of reservation price was no longer significant. None of the higher order interactions were significant in this case. In general, results of this additional analysis corroborate our findings above, and are available from the first author upon request.

According to Hypothesis 7, experienced bidders should be more susceptible to bid first for listings with zero-bids, finding hitherto overlooked listings. Because experience ratings of only winning bidders were available to test this hypothesis, we compared the experience of winners of completed auctions receiving a single and two bids. Hypothesis 7 would be supported if winners of single-bid auctions had more experience than those of two-bid auctions. In the data set, 75 listings were classified as receiving a single bid with winning bidder experience also available, while 106 listings received two bids. A one-way ANOVA was conducted with two levels of number of bids (single, two) as the independent factor, and the experience of the winning bidder as the dependent variable. The main effect of number of bids was significant [$F(1,179) = 5.04, p<0.05$]. Winners of single-bid auctions were significantly more experienced ($M_{\text{single-bid}} = 128$) when compared to winners of two-bid auctions ($M_{\text{two-bids}} = 61.7$), providing statistical support to Hypothesis 6. Future research may corroborate this result by examining the bidding strategies of experienced and novice bidders in a longitudinal format—data that were not available to us.

An alternative possibility that could account for these results is that the first bid placed may have been outrageously high—dissuading other bidders from competing. Such a strategy pursued over time may result in the buyer winning auctions systematically, and augment his/her experience rating as well. To verify if this was the case, we examined the prices paid by winners of the single-bid and two-bid auctions. A one-way ANOVA showed that this difference was not significant [$M_{\text{single-bid}} = \text{US}\$28.8 vs. $M_{\text{two-bids}} = \text{US}\$24.2, F(1,179) = 0.85, p>0.3$]. This analysis suggests that over-bidding did not appear to be a significant strategy adopted by winners of single-bid auctions.

The results and the reasoning underlying Hypotheses 6 and 7 suggest that experienced bidders would tend to stay away from extremely popular digital auctions, with a large number of bids and/or unique bidders. To further verify that this was the case, first,
the correlation coefficient between total number of bids and the experience rating of the winning bidder was computed. It was found to be \(-0.186\) (\(p < 0.001\)), indicating that as the total number of bids for a listing increase, the winning bidder tends to be less experienced. Second, we also computed the correlation coefficient between number of unique bidders and experience of the winning bidder. In this case, it was \(-0.11\) (\(p < 0.001\)). Taken together, these analyses suggest that with experience, bidders appear to be less interested in hotly contested, greatly popular listings. Instead, they may seek hitherto overlooked listings, thereby benefiting from the herding bias.

6. General discussion

6.1. Herding bias as a context-induced bias

The research presented here deepens the understanding of the processes through which the herding bias occurs in digital auctions. The operation of this bias implies that, just as in traditional exchange arenas, buyers participating in these so-called efficient digital marketplaces routinely violate principles of value maximization and consistency, and make sub-optimal bidding decisions. Behavioral decision research has shown that in many instances, consumers make use of, and are influenced by, contextual informational cues when making choices—typically, environmental factors or irrelevant attributes—and exhibit inconsistent preferences in different choice contexts. Such deviations have been labeled as “context-induced biases” (e.g., Dholakia, 2002; Simonson & Tversky, 1992). The herding bias, in our opinion, represents a type of context-induced bias occurring in a naturalistic setting, in the sense that the combination of auction environment attributes—a large number of alternatives, multiple sources of uncertainty, importance of seller trustworthiness, and ease of observing others’ behavior at prescreening—together create the context that drives the occurrence of this bias.

Research on context-induced biases shows that such effects can arise from two sources: either from the characteristics of the task itself (called “local” effects), or from the context created by previous tasks (called “background” effects). Throughout this research, we have implicitly assumed that the herding bias is driven by a local effect—that is, individual bidders become susceptible to this bias due to constructive hierarchical choices on entering the auction space, and using information available to them on entering. However, it is plausible that the bias may also operate or be aided by the remembrance of previously made bidding choices and the selection criteria used, such as the “others-observed-behavior” heuristic in the past—and thereby reflect a background context-induced bias. This issue warrants further investigation, and the determinants of background context operation on occurrence of the herding bias need to be ascertained.

We suggested that the influence of other bidders’ behavior may operate as a primary determinant of the herding bias. In addition, research on conformity-preserving processes in psychology suggests that once bidders bid on a listing, they become more committed to winning it, presumably from endowment effects (Thaler, Kahneman, & Knetsch, 1992), or the sunk cost effect (Arkes, 1991), or both. Such a spiraling escalation may in fact perpetuate, as well as magnify the bias, elevating the final price of coveted listings even further, and keeping overlooked listings so, until the very end. Disentangling the scope of operation and the relative influence of the herding bias itself, from the subsequent escalation, is a promising avenue for future research.

6.2. Practical implications for participants and organizers

From a practical standpoint, the research reported here provides guidance to participants and organizers of digital auctions. One interesting result of the study is that both the likelihood of being overlooked and that of being coveted change systematically with listing volume. The chances of being overlooked are relatively high while those of being coveted are low, at light and heavy listing volumes, suggesting that savvy buyers have more opportunities to benefit from herding bias occurrence in these circumstances. In contrast, at medium volumes, chances of being coveted are relatively high, and those of being overlooked are low, affording better opportunities for sellers to benefit (see Fig. 1). Buyers and sellers may select categories within digital auctions to bid and list, respectively, based on volume, to manage such outcomes.
We also showed that with experience, buyers become more savvy, and amenable to stay away from, or drop out of hotly contested auctions, and more likely to find hitherto overlooked listings. The specific psychological mechanisms that enable this change to occur warrant further research—perhaps through a controlled experimental methodology. We also showed that with experience, sellers became less susceptible to the negative consequences of the herding bias—crossing the Rubicon of receiving the first bid. For buyers, posting a reservation price when listing an offering was shown to be one mechanism for reducing the likelihood of being overlooked, and increasing the possibility of becoming coveted. Interestingly, experienced buyers did not systematically appear to take advantage of either auction attribute, suggesting added opportunities for them to minimize bias susceptibility. Further, the question still remains as to what other specific factors, especially auction environment attributes, allow this hurdle to be crossed, and deserves future research attention. Such research is likely to be especially useful for sellers, giving them specific guidance for listing their products successfully in digital auctions.

This research also speaks to organizers of digital auctions. While we focused on legitimate and ethical, listing and bidding behaviors, the findings reported here do suggest that fraudulent practices, such as “shilling”, that is, placing bids on one’s own listings, falsely inflating experience ratings, etc. (Schuyler, 2000) may have a potent indirect influence on auction outcomes, on account of the herding bias. Teasing apart the direct and herding-bias-related effects of such fraudulent practices requires additional attention. The findings also point to the consideration of education of auction participants by organizers. Such education may range from providing a generic FAQ-type description of this bias, to actively and individually training participants regarding its mechanisms and implications through one-to-one communication—facilitating correction processes which are discussed next (Arkes, 1991).

### 6.3. Correction processes

Recent research in social judgment and behavioral decision making has begun to examine correction processes—the psychological processes and their correlates through which individuals correct for context-induced biases, and make more accurate, normatively consistent judgments and choices (e.g., Arkes, 1991; Petty & Wegener, 1992). This line of research shows that when decision makers are sufficiently motivated and able, and when they realize the influence of irrelevant contextual factors, they engage in debiasing processes to counteract these influences, reducing the magnitude of context-induced biases. Arkes (1991) suggests that judgments can be improved by raising the cost of using the sub-optimal judgment strategy—resulting in the utilization of available information more thoroughly. Consistent with this, earlier research has shown that the rate of occurrence of the herding bias declines as price of auction listings increases (Dholakia & Soltyssinski, 2001).

We studied the role of ability in this research—operationalized by the previous experience of the buyer. But it is also likely that various motivating factors such as particular mind-sets, that is, cognitive orientations with specific processing objectives, mood-states, degree of involvement, or availability of time will determine the extent of bias correction for buyers. Exploring these, and the interactions between motivational and ability factors, is likely to be a fruitful extension to this research. In the same way, studying the role of dispositional attributes (such as the need to conform) on buyer susceptibility to the herding bias is also important.

### 7. Mindfulness of bias occurrence

We have implicitly assumed in our discussion that the bias is initiated through a mindful mechanism, that of observing and using others’ behavior to guide one’s own. It may be fruitful to verify this assumption, and to disentangle the differential effects of non-conscious psychological processes on bias operation. Further, understanding the role of non-conscious priming processes in accentuating or dissipating this bias needs greater attention. For instance, recent research shows that conformity can be elicited or suppressed by nonconscious priming (Epley & Gilovich, 1999), suggesting that sellers may be able to use appropriate priming strategies to get over the “first bid hurdle” and succeed in making their listings coveted. As an example, including primes such as “follow”, “com-
pete”, or even an arrow “⇒” icon in the listing’s title pointing toward the number of existing bids may be sufficient to prime herding behaviors in bidders. An exploration of suitable primes for eliciting either bias-favoring or bias-disfavoring responses warrants further investigation.

To summarize, this research shows that even though the herding bias is prevalent in digital auctions, individual buyers and sellers can take specific actions to become less susceptible, especially to its negative consequences and to benefit from its positive consequences, thereby drawing closer to the “efficient market” ideal that has so characterized the popular view of digital auctions.

Acknowledgements

We thank Sudhakar Vissa for his help with data collection and analysis, and the editor and the three reviewers for their insightful and constructive comments on earlier drafts of this article.

Appendix A. Details of coding scheme using the Mexican Pottery example

A detailed discussion of the coding scheme is provided here to both enable greater understanding, as well as to facilitate future research in this area. We use the example of the Mexican pottery product category since it is presumably the most difficult to code. In coding the auction listings as coveted or overlooked, we classified each product category into sub-categories. Mexican pottery was classified into the following 26 different types, so that lots were maximally similar and comparable before actual comparisons were done:

1. Single bowl
2. Multiple bowls (Nesting)
3. Single plate
4. Multiple plates
5. Animal
6. Pitcher/jug
7. Single vase/planter
8. Multiple vases/planters
9. Pots—casserole
10. Salt and pepper shakers
11. Ashtray
12. Miscellaneous pottery
13. Bank
14. Wall hanging
15. Pictures/paintings
16. Box/jar with lid
17. Single cup/mug
18. Multiple cups/mugs
19. Coffee/tea server
20. Tree of life
21. Platter/charger
22. Picture frame
23. Cross
24. People (figure)
25. Tile
26. Candleholder

In the second stage, we developed a number of objective, verifiable conditions to facilitate comparisons. For instance:

- Larger-sized pottery within the same sub-category is better than smaller sized pottery.
- Chipped/dented/broken pottery is worse than pottery in good condition.
- Signed pottery is better than unsigned pottery.
- Glazed pottery is better than unglazed pottery.
- Hand-painted pottery is better than machine-painted pottery.

and so on. Then, the judges used these rules to qualitatively and globally determine the outcome of comparisons. Note that in practice, the task was made much simpler since one clearly superior overlooked listing in a particular group could be compared to several listings in the same group within the requisite time-frame. The same procedure and outcome applied for inferior coveted listings. This approach to coding and classification is used in qualitative research often (see Strauss & Corbin, 1990 for a detailed exposition).

References


