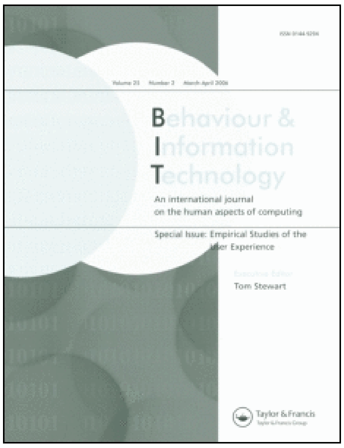

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Kholekile L. Gwebu[a]; Michael Y. Hu[b]; Murali S. Shanker[c]
[a] Department of Decision Sciences, University of New Hampshire, Durham, NH, USA [b] Department of Marketing, Kent State University, Kent, OH, USA [c] Department of Management Information Systems, Kent State University, Kent, OH, USA

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An experimental investigation into the effects of information revelation in multi-attribute reverse auctions

Kholekile L. Gwebu[a]*, Michael Y. Hu[b] and Murali S. Shanker[c]

[a]*Department of Decision Sciences, University of New Hampshire, , 15 Academic Way, McConnell Hall, Durham, NH 03824, USA;* [b]*Department of Marketing, Kent State University, College of Business, Kent, OH 44240, USA;* [c]*Department of Management Information Systems, Kent State University, College of Business, Kent, OH 44240, USA*

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Bid-takers in multi-attribute reverse auctions (MRA) are typically confronted with a myriad of information revelation options and must make decisions on which pieces of information to reveal to bidders and which ones to conceal. This study explores how the choice of different types and combinations of information can affect bidding behaviour and bidder perceptions in MRA. The results of a computer-based laboratory experiment suggest that by reducing the level of information asymmetry and using certain combinations of information a bid-taker can reduce bidder drop-out and spur the submission of high quality bids, i.e. bids that yield high levels of utility for the bid-taker.

Keywords: e-commerce; e-auction; information revelation; information processing; multi-attribute reverse auction

1. Introduction

Today, auctions play an important role in business-to-business (B2B) electronic commerce (Wang *et al.* 2001, Bandyopadhyay *et al.* 2008, Pekeč and Tsetlin 2008). With the advent of the Internet, complex auction mechanisms that permit buyers and sellers to engage in multifaceted negotiations have emerged. One such mechanism is the multi-attribute reverse auction (MRA). MRAs are procurement auctions that enable buyers (bid-takers) to award contracts via a competitive bidding process to a seller (bidder) who submits the best bid on several pre-determined attributes of an item (Beil and Wein 2003, Chen-Ritzo *et al.* 2005). They are an extension of single-attribute reverse auctions (SRA), and have recently begun to receive attention primarily due to their potential to overcome some of the major well-documented shortcomings of SRA (Koppius 2002, Teich *et al.* 2004, Bichler and Kalagnanam 2005, Chen-Ritzo *et al.* 2005, David *et al.* 2006).

MRAs are gaining prominence among practitioners (Kafka *et al.* 2000). In fact a market analysis of 125 European and American firms conducted by the Aberdeen Group (2002) revealed that when evaluating e-sourcing solutions many firms (73% European, 45% American) looked for solutions that support multi-attribute automated negotiations. However, despite their growing popularity there are still a number of unresolved issues surrounding the optimisation of MRA performance. One key issue involves the effect of information on auction performance. Recently, there have been several calls for research that examines the effects of information on MRA performance (Teich *et al.* 2006, Arora *et al.* 2007, Zhang and Jin 2007). Indeed, in a recent article which reviews procurement auction research and its applications, Rothkopf and Whinston (2007) state that 'studies of the impacts of the feedback offered to bidders and different feedback policies would be an important future extension.' The current study is in response to such calls. Specifically, it examines whether different types of information impact bidder perceptions and the quality of bids as these subsequently determine first-score MRA performance. The bidder perceptions considered include the perceived likelihood of wining the auction (measured on a 0% to 100% scale), i.e. the degree to which bidders believe that they are going to win the auction, and the perceived usefulness of the information received (measured on a 0% to 100% scale), i.e. the degree to which bidders believe that the information that they receive is useful for bidding purposes. The bid quality is determined by the utility that the combination of attributes in a bid gives the bid-taker. The higher the utility – the better the bid quality.

Information is important in auctions because it has the potential to support bid construction (Teich *et al.* 2004, 2006). In MRA, information may play an even more prominent role because bidders are required to construct multidimensional bids. Oftentimes, the

*Corresponding author. Email: khole.gwebu@unh.edu

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bid-taker controls information flows including the type and amount of information acquired by bidders. Depending on the information revelation policy adopted by the bid-taker, bidders may or may not be able to acquire certain pieces of information. In an attempt to protect themselves, some bid-takers adopt conservative information revelation policies that limit bidders to only a few pieces of information, while others are more liberal in the information that they reveal (Koppius 2002). For instance, they may reveal information about their utility function that indicates their preferences for different attribute value combinations. They may also reveal information about the number of competing bidders, the bids submitted by each bidder, the actions a bidder can take to improve on a previously submitted bid, or the bid rankings. The question we seek to answer in this study is 'How do bidders react to the different pieces of information that they acquire in a first-score MRA?'

Given the myriad of information revelation policies available in contemporary MRA platforms, answers to the above research question will aid practitioners in the design of auction information revelation policies. The current study extends existing literature by considering a wide range of information revelation policies and examining their effects on both bidder perceptions and the quality of bids submitted. Such knowledge is critical because without fully understanding the consequences of different information revelation policies, MRA practitioners may unintentionally undermine their own efforts by inadvertently adopting a sub-optimal information revelation policy.

The article is structured as follows. The next section presents a review of related work and highlights some of the limitations of prior research. Drawing on research from signalling theory, we proceed to develop a conceptual framework that provides insight into the relationship between information revelation, bidder perceptions and bid quality. A laboratory experiment is then conducted to empirically evaluate the proposed framework. Finally, the conclusions and limitations of this study are presented, followed by directions for future research.

2. Related work

To date, much of the work on MRA primarily consists of game-theoretical models (e.g. Beil and Wein 2003, Bichler and Kalagnanam 2005, Parkes and Kalagnanam 2005, De Smet 2007). However, experimental research using human subjects is important for understanding issues surrounding bidder behaviour and auction performance (Bichler 2000).

Current experimental studies have considered two main issues surrounding MRA design: (1) whether MRA can be designed to outperform SRA in terms of measures such as bid-taker utility and auction efficiency (Bichler 2000, Chen-Ritzo *et al*. 2005) and (2) to understand the impact of certain information cues on MRA performance (Koppius 2002, Strecker and Seifert 2003, Chen-Ritzo *et al*. 2005). Researchers who have considered the latter issue suggest that information provided to bidders may positively impact bid-taker utility, bidders' profit, auction efficiency and Pareto-optimality. For instance, Chen-Ritzo *et al*. (2005) use an approach involving the release of marginal improvement values for each attribute that alerts individual bidders on how they can improve on previously placed bids. This information results in bids that yield high levels of utility for a bid-taker. Strecker and Seifert (2003) test the effects of providing bidders with a bid-taker's preference information. They find that when preference information is revealed, MRAs are more efficient than when it is concealed. Koppius (2002) conducts a computer-based laboratory experiment to analyse the effects of two information revelation policies (unrestricted versus restrictive) on MRA efficiency and Pareto-optimality. The unrestricted policy exposes bidders to information about the highest bid, all bids submitted in a previous auction round, and the relative scores of each of the most recently submitted bids. The restricted policy only exposes bidders to information about the highest bid. He finds that MRAs with an unrestricted information revelation policy outperform those with restricted ones on both efficiency and Pareto-optimality.

While these prior studies do provide some valuable insights into the effects of information revelation policies on MRA, they are limited in scope since they examine only one or two broad revelation policies and other, possibly better, policies are yet to be explored. Further, they only focus on bid-taker related performance measures such as bidder utility, efficiency and Pareto-optimality without considering the effects of information elements on bidder-related measures, such as the bidders' perceived usefulness of the information, or their perceived likelihood of winning the MRA. However, prior literature strongly suggests that understanding bidder perceptions is important (Chakravarti *et al*. 2002, Weinberg and Davis 2005). Specifically, perceived usefulness has been found to be directly associated with use in various contexts (Rai *et al*. 2002, Bhattacherjee and Premkumar 2004). In auctions, bidders are unlikely to use information provided to them unless they perceive it to be useful. Therefore, provision of information that bidders perceive to be useful is essential in supporting the construction of high-quality bids. Understanding bidders' *perceived likelihood of winning* an auction is also important (Ward and Chapman 1988, Skitmore 2004). In the case of iterative auctions such as those considered in this study, the perceived likelihood of winning in one stage of the auction may determine the likelihood a bidder will stay in the auction and the degree of participation in subsequent stages (Malhotra 2010). If bidders perceive a reasonable chance of winning, they are more inclined to compete aggressively in subsequent stages otherwise they may drop out of the auction altogether. Thus, in order to minimise bidder drop-out and maximise bid-taker utility, bid-takers need to ensure that bidders perceive a reasonable chance of winning.

To encapsulate, prior studies have provided some important insights on the role of certain information elements on MRA performance. However, few comparative empirical analyses exist that examine the effects of several types of information on auction performance (Teich *et al.* 2006). Further, as bidder perceptions may significantly influence MRA auction participation, bidding behaviour, and subsequently auction performance, it is important for researchers to study them. Consequently, our study addresses these important limitations by (1) examining the effect of various information elements on bidders' *perceived usefulness* of information they receive for bid construction and *perceived likelihood of winning* the auction and (2) comparing the impact of different information elements on *bid-taker utility*. The next section draws on signalling theory as the theoretical backdrop to discuss the relationship between the various information elements and the outcome measures considered in this study.

3. Hypothesis development

MRA are characterised by *information asymmetry* between the bid-taker and bidders (Arora *et al.* 2007). Information asymmetry exists when one party to a transaction has more or better quality information than the other party (Akerlof 1970, Lofgren *et al.* 2002). While bidders normally control information about their underlying cost for each attribute combination, in MRA, the bid-taker typically has more and better quality information than bidders including the information about his or her utility function indicating the preferred bid values for each attribute combination, the values submitted for each attribute in a bid by bidders, the bid rankings, the number and identities of participating bidders, the improvement path detailing how bidders can improve on previously placed bids, and the auction rules and procedures. Markets that exhibit such information asymmetries can suffer drastically and even fail, because the party at an information disadvantage could make poor decisions (Akerlof 1970, Lofgren *et al.* 2002). This phenomenon is known as *adverse selection*, and is potentially a significant source of market inefficiency in auctions due to inherent information asymmetries at the time of auction transactions (Dewan and Hsu 2004).

Signalling is one effective way to mitigate the adverse effects of information asymmetry (Spence 1973). It is a process where the party at an information advantage takes observable actions to make certain information elements available to assist the less informed party to make better decisions. Once a signal has been relayed to the less informed party, it is interpreted, and inferences about a course of action to take are drawn by the less informed party based on the signal(s). The theory of signalling has been widely applied to markets where information asymmetry and adverse selection are present (Mishra *et al.* 1998, Deutsch and Ross 2003, Shen and Reuer 2005). In the auction literature, most of the previous analyses of the effects of signalling have been exclusively conducted in the context of single-attribute auctions (Jap 2003, Engelbrecht-Wiggans and Katok 2006, Mithas and Jones 2007). However, MRA differ from single-attribute auctions in a number of important ways, which warrant the current investigation. For instance, the buyer (bid-taker) rather than the seller has an information advantage. Consequently, some of the information elements that can be revealed in MRA differ significantly from those that can be revealed in single-attribute auctions. Hence, the findings of single attribute auction studies may not be fully applicable to the MRA context. Additionally, bidding decisions in MRA are more complex in nature, and demand greater cognitive effort on the part of bidders compared to bidding decisions made in single-attribute auctions. In MRA, bidders are required to engage in multi-criteria decision-making under competitive conditions, rather than bidding only on a single criterion such as price in single-attribute auctions. Thus, bidders are more likely to make poor bid choices in MRA than in single-attribute auctions, and the effects of poor bid choices may be more severe in MRA. This study extends the investigation of information asymmetry from the single-attribute auctions setting to MRA. However, the intention of this research is not to contrast the effects of signals in MRA to the effects of signals in single-attribute auctions, but rather to understand how the revelation of various signals in MRA affects bidder perceptions and bid quality.

3.1. Signals in MRA

Bidding in MRA entails submitting a combination of values on a set of attributes (pre-selected by the bid-taker) over a course of time. The minimum information required to submit a bid (i.e. participate) is the set of auction rules and procedures. In our study, we call this information *Minimum Information*. Information asymmetry between the bid-taker and bidders tends to be high when bidders are provided with *Minimum Information* because bidders must speculate on the attribute value combinations (bid) that not only fulfil the preferences of the bid-taker, but also outperform competitors' bids. Moreover, Minimum Information MRA bidders may also need: (i) *preference signals* and (ii) *state-of-competition (SOC) signals* in order to optimise their bids. Preference signals provide information about the bid-taker's preferences for the various attribute value combinations. If they are presented explicitly they can take the form of the bid-taker's weighting of each of the attributes under consideration. If they are presented discretely, they can take the form of private customised recommendations which tell the bidder to make improvements to a previously submitted bid, e.g. 'to improve your previous bid keep the value on attribute x constant and change the value on attribute y'. SOC signals, on the other hand, provide information about competing bidders, e.g. the number of competing bidders, the values of the bids placed by all the bidders and the rankings of the bids.

Hence, the bid-taker in an MRA has the option of *Partial Information Revelation*, i.e. revealing either the preference signals, *or* the SOC signals, but not both or *Full Information Revelation*, i.e. revealing both preference signal *and* SOC signals. Under *Partial Information Revelation*, there are varying approaches to disclose preference information: Explicit Preference signalling where the bid-taker publicly discloses attribute value preferences in the form of a utility function to all the bidders (Koppius 2002, Strecker and Seifert 2003), or Discrete Preference signalling where bid-takers privately inform each bidder on how to make improvements on their previously placed bids (Teich and Wallenius 1999, Chen-Ritzo *et al*. 2005). The following sections examine the effects of each of the three different Partial Information Revelation approaches identified above, i.e. Explicit Preference signals, Discrete Preference signals and SOC signals on the outcome measures considered in this study. Thereafter, we consider the effects of Full Information Revelation versus Partial Information Revelation.

3.2. Minimum Information vs. signalling

When an Explicit Preference signalling approach is adopted, bidders can accurately deduce the level of utility that any attribute value combination provides to the bid-taker. Thus, the Explicit Preference signal lessens the chance of poor bid choices by exposing inappropriate bids, and allowing bidders to focus on bids that are more likely to satisfy the bid-taker. For the bid-taker, the bids received after preferences are relayed to bidders are likely to be of a higher quality than when bidders have Minimum Information. In the literature, utility scores are often used to measure the quality of bids (Bichler 2000, Koppius 2002, Strecker and Seifert 2003). Essentially, they are a measure of the similarity between the bid values submitted by bidders and those desired by the bid-taker with higher utility scores preferable to lower ones. We expect Explicit Preference signalling to trigger the submission of higher utility scores than Minimum Information. Moreover, since Explicit Preference signals reduce the cognitive effort required to construct a high-quality bid, bidders are likely to find them more useful than Minimum Information for bid construction purposes. Bidders are also likely to feel more confident in their chance of winning and be less likely to drop out of the auction compared to situations when they are provided with Minimum Information, since the level of uncertainty about the quality of the bids required to win the auction is reduced in the presence of explicit signalling.

However, despite the potential benefits of explicitly revealing a bid-taker's utility function there are several concerns with this approach (Strecker and Seifert 2003, Chen-Ritzo *et al*. 2005). For instance, bid-takers may not be capable of expressing a utility function (Chen-Ritzo *et al*. 2005). Additionally, prior studies have also suggested that bid-takers often fear that bidders can exploit this information and shift the gains of trade to themselves at the expense of the bid-taker (Strecker and Seifert 2003). Moreover, some of the information contained in a utility function may be of a sensitive nature, thus bid-takers may have security concerns surrounding the release of Explicit Preference signals to bidders (Chen-Ritzo *et al*. 2005). Therefore, some have advocated for the use of Discrete Preference signalling techniques rather than Explicit Preference signalling (Chen-Ritzo *et al*. 2005).

Discrete Preference signals are customised recommendations provided to each bidder by the bid-taker that do not explicitly specify the bid-taker's utility function, but indicate how a bidder can improve on a previously placed bid. Discrete Preference signals may take different forms. For instance, Chen-Ritzo *et al*. (2005) use a technique that involves providing bidders with marginal values for each attribute that indicate how they can improve on previously placed bids, while Teich *et al*. (2001, 2006) discuss a technique they use in their MRA application (NegotiAuction) where individual bidders are alerted on how they can vary price to improve on previously placed bids. Our study examines the effects of one of the simplest forms of Discrete Preference signalling. It is a technique that entails the bid-taker privately alerting each bidder, after a bid, which attribute requires the most improvement in the subsequent bid in order to improve the bid-taker's utility. Our goal is to examine whether a very basic form of Discrete Preference signalling can be as effective as SOC signals in improving bids and bidder perception over the Minimum Information. If it can, then more complex forms of Discrete Preference signalling could potentially yield even better results. Bidders may find such a signal to be useful for bid construction purposes as it reduces uncertainty, and increases the probability of the bid being accepted by the bid-taker. Moreover, since the level of uncertainty about the quality of their bids can be reduced by a Discrete Preference signal, bidders are also likely to feel more confident about their chances of winning the auction compared to when they have Minimum Information.

SOC signals may play a key role in enabling bidders to optimise their bids. SOC signals include bid rankings for each auction round, and the bid values for each attribute submitted by other bidders. Further, the bidders' identities can also be provided. SOC signals can have two main effects on bidders: (i) a *competitive* effect and (ii) a *guiding* effect (Ward and Chapman 1988, Johns and Zaichkowsky 2003). The competitive effect of SOC signals stems from having a single winner in an MRA. If bidders can observe the actions of other bidders, this can stimulate competitive bidding behaviour. Since all non-winning participants make no profits, but incur participation costs, it is optimal for bidders to submit bids that they believe will give them the highest likelihood of winning the auction and profiting from the subsequent transaction. Merely considering the bid-taker's preferences is insufficient to win, because preference signals do not factor in the competitive nature of the auction. For bidders to construct bids of superior quality than their competitors, it is important for them to also observe and understand their competitors' bidding behaviour. From the bid-taker's perspective, this information applies competitive pressure among bidders to improve their bids.

The guiding effect stems from the fact that, indirectly, SOC signals provide bidders with the bid-taker's preferences. If a bidder examines bid rankings along with bid values submitted by other bidders, they can deduce the types of bids the bid-taker prefers, as bid rankings are based on the bid-taker's preferences. The closer a bid is to the bid-taker's preferences, the higher it will be ranked. Thus, in subsequent auction rounds, bidders can attempt to submit bids that are of superior quality than previous top-ranked bids.

SOC signals are expected to have a motivational effect on bidders. For bidders who view an SOC signal that ranks their bids high, this will likely reinforce bidding behaviour and improve their confidence in their chance to win the auction. For bidders who view an SOC signal that ranks their bid low, this will likely spur them to re-evaluate past bids and take corrective actions. In either case, they can act on the SOC information and have more confidence in the quality of their new bids and the probability of their new bid winning the auction.

While it is possible that bidders can be discouraged by SOC signals because their cost structure does not allow them to compete with the current winning bids, we expect this effect to be less dominant than the motivational effect. This is because bidders who are invited to participate in B2B reverse auctions are often prescreened and hence are competitive in terms of their cost structure.

Given these effects of SOC signals, bidders exposed to them should find them more useful than Minimum Information. Moreover, these signals should lead to better quality bids, and bidders should have greater confidence in their ability to win the auction compared to when they have Minimum Information.

Based on all the above stated arguments, we hypothesise that:

> H_{1a}: Bidders with Explicit Preference, Discrete Preference or SOC signals will submit bids that yield higher utility scores than bids submitted by bidders with Minimum Information.
>
> H_{1b}: Bidders will find Explicit Preference, Discrete Preference or SOC signals more useful for bid construction purposes than Minimum Information.
>
> H_{1c}: Bidders with Explicit Preference, Discrete Preference or SOC signals will perceive a higher likelihood of winning an MRA than bidders with Minimum Information.

3.3. Discrete preference vs. state-of-competition signals

While Discrete Preference and SOC signals should both have a positive impact on bidder perceptions and behaviour, at times, a bid-taker is willing to reveal only one of these signals. For instance if the bid-taker does not want to reveal the identity of the bidders, then a Discrete Preference signal would be desirable. Whereas if the bid-taker does not want to customise signals, then SOC signals could be desirable. Thus, it would be of interest to determine which one of these two signals results in better auction performance and bidder perceptions of usefulness and likelihood of winning.

In the previous section, it was suggested that SOC signals can stimulate both competitive bidding behaviour, and also implicitly guide bidders towards the preferences of the bid-taker, while Discrete Preference signals only guide bidders towards the preferences of the bid-taker. Thus, we expect that bidders receiving

SOC signals will submit better quality bids, perceive information to be more useful, and have a perception of higher likelihood of winning than those bidders receiving Discrete Preference signals. Therefore, we hypothesise that:

H_{2a}: Bidders with SOC signals will submit bids with higher utility scores than bidders with Discrete Preference signals.

H_{2b}: Bidders with SOC signals will perceive such signals as being more useful than bidders with Discrete Preference signals.

H_{2c}: Bidders with SOC signals will perceive a higher likelihood of winning an MRA than bidders with Discrete Preference signals.

3.4. *Partial vs. Full Revelation*

When bidders in MRA are exposed to Discrete Preference, Explicit Preference and SOC signals, we term this *Full Revelation*. In such situations, the likelihood of poor bid selection is low, as bidders have all the necessary signals to construct bids that satisfy both the preferences of the bid-taker, and to outperform competitors. Therefore, given all the necessary information to bid effectively, bidders are likely to find the signals more useful, and be more confident in their likelihood of winning, than if they only have *Partial* information (i.e. some of the signals but not all) or *Minimum* information. Moreover, Full Revelation is also likely to lead to higher quality bids. Therefore, we hypothesise that:

H_{3a}: Bidders will submit bids with higher utility scores when the bid-taker adopts a policy of Full Revelation compared to when the bid-taker adopts a Partial or Minimum Revelation policy.

H_{3b}: Bidders will perceive the combination of the signals they receive as being more useful when the bid-taker adopts a policy of Full Revelation compared to when the bid-taker adopts a Partial or Minimum Revelation policy.

H_{3c}: Bidders will perceive a higher likelihood of winning when the bid-taker adopts a policy of Full Revelation compared to when the bid-taker adopts a Partial or Minimum Revelation policy.

4. Method

4.1. *Experimental design*

To test the hypotheses, an experiment was designed around a three stage first-score MRA with a hard closing rule. While many different auction configurations could have been chosen, a multi-stage format (Teich *et al.* 2004) is employed here because it has been commonly used in practice to trade items as diverse as timber rights, art and real estate (Engelbrecht-Wiggans 1998, Olivier and Philippe 2007), and it readily permits the evaluation of different types, combinations and amounts of information on bidders' behaviour and perceptions. Typically, this type of mechanism works as follows. At the first stage, a bid-taker has the option of revealing to the bidders some baseline information, i.e. auction rules, procedures and bidders preferences for different attribute combinations (Explicit Preference signals) or only revealing the auction rules and procedures, i.e. Minimum Information. Accordingly, the experiment is designed to expose some bidders to Explicit Preference signals and others to Minimum Information during the first stage of bidding. Bid-takers can only collect and evaluate the bids received after the first stage of bidding. Thereafter, they must decide whether or not to reveal any of the information received from the bids to the bidders. If the bid-takers choose to reveal the information, they can either display all the information received (i.e. SOC: the number of bids received, the bid values for each attribute, the ranking of the bids) to all the bidders or they can filter, summarise and customise the information then reveal it privately to each bidder (Discrete Preference signal). Thus, in the experimental design three treatment conditions are included during the second stage of bidding; an SOC condition if a bid-taker chooses to reveal all the information concerning the bids received, a Discrete Preference condition if the bid-taker chooses to summarise the bid information and make a customised recommendation to each bidder privately on how to make improvements to their previous bids, and a Minimum Information condition if a bidder chooses not to reveal any information concerning the bids received.

During the course of the auction, bid-takers can choose to continue providing the bidders with the same signals or they can change the signals. Since this study seeks to also explore the effects of varying signals and having different signal combinations the signals are switched between the second and third stage of the auction such that bidders who received SOC signals during the second stage received Discrete Preference signals during the third stage and vice versa. An added bonus of this design is that it also permits the evaluation of the effects of different sequences of signals.

While it is possible for bid-takers to misrepresent their utility function the goal of the study is not to examine the effects of signal misrepresentation. Rather, the signals were truthfully revealed to bidders and we focused on studying the effects of these signals on bidder perceptions and behaviour. Like Chen-Ritzo *et al.* (2005), the bidders were made aware that the signals that the bid-taker was revealing were genuine, thus the issue of misrepresentation was not a major concern in this study.

A summary of the experimental design is shown in Figure 1. Based on the above-described conditions, six treatment groups were created. In each treatment group, six auctions were created then four subjects were randomly assigned to compete against each other in an auction. Therefore, we have a balanced experimental design.

4.2. *The MRA simulator and experimental procedure*

Following the experimental design, a first-score MRA simulator that releases different pieces of information at different stages of the auction was constructed. As information is released and bidders assimilate it, their perceptions and bids were assessed. The experiment revolves around a scenario where a bid-taker (buyer), represented by a computer program, wants to procure a computer from one of four bidders (human subjects). The four bidders log on to a bid-taker's auction website and compete by entering values for three preselected attributes, *hard-drive, memory* and *price*, over the course of three auction rounds. During each of the three auction rounds, the bid-taker reveals different signals to the bidders.

The subjects were undergraduate students across a range of study disciplines including Accounting, Economics, Finance, Marketing and Management and Information Systems at a large university. Consistent with related studies (Koppius 2002, Strecker and Seifert 2003), upon arrival at the laboratory, subjects were trained, and then randomly assigned to visually isolated computer terminals.

The training session commenced with a presentation providing a detailed description of the multi-stage MRA mechanism, scenario, software, and rules and procedures. The subjects then watched a training video that walked them through the entire bidding process. Thereafter, an online quiz was administered to assess the subjects' understanding of the scenario, auction rules and procedures, and their ability to use the multi-stage MRA software correctly. Only subjects who correctly answered all questions on the quiz were allowed to proceed to the next stage of the experiment. A total of 144 subjects answered all the quiz questions correctly. Next, these subjects were provided with a written copy of the experiment instructions, and a cost schedule, which indicated the cost they would incur for each submitted bid (Strecker and Seifert 2003, Chen-Ritzo *et al*. 2005). To allow the subjects to anticipate forthcoming information (Hu and Toh 1995), the written copy of the experiment instructions showed the signal sequence for each auction round. The subjects then logged onto the system to enter demographic information. Bidding commenced when all four bidders of the same group finished entering their demographic information.

During each auction round, the subjects were provided with various signals. The signals received by each bidder are discussed in the experimental design section. Signals were displayed on a bidding screen and varied depending on the treatment administered. All bidding screens consisted of four sections: a *profile* section, a *bidding* section, a *profit or loss* computation section and a *signal revelation* section.

The computation of a profit or loss for a bidder is based on the values selected in the bidding section and the bidder's cost for each of the attributes, as was indicated in the bidders' cost schedule. Bidders were free to alternate between the bidding section and the profit or loss computation section to determine their

Group	Stage 1	Stage 2	Stage 3	
1	Explicit Preference	State of Competition	Discrete Preference	Full Revelation
2	Explicit Preference	Discrete Preference	State of Competition	
3	Explicit Preference	Minimum Information	Minimum Information	Partial Revelation
4	Minimum Information	State of Competition	Discrete Preference	
5	Minimum Information	Discrete Preference	State of Competition	
6	Minimum Information	Minimum Information	Minimum Information	Minimum Revelation

Figure 1. Experimental design – signals disclosed.

payoffs from various attribute combinations. Once satisfied, they submitted their bid by clicking *Place Bid*. To minimise accidental bidding, a control mechanism is incorporated in the software that prompted bidders to confirm their bids before submission.

Bidders competed in each auction round by submitting a bid $\beta_i = (x_1, x_2, x_3)$ on three attributes *hard-drive* (x_1), *memory* (x_2) and *price* (x_3). Consistent with Bichler (2001), upon receiving bids, the bid-taker evaluated each bid against its utility function represented by $U(\beta_i) = \sum_{i=1}^{n} w_i S(x_i)$ where w_i is the weight assigned to attribute x_i such that $0 < w_i < 1$ and $\sum_{i=1}^{n} w_i = 1$. Individual attributes were scored using the function $S(x_i) = \frac{x_i - x_{\text{worst}}}{x_{\text{best}} - x_{\text{worst}}}$ where x_{worst} and x_{best} are bid-taker's least and most desired values respectively for x_i (Bichler 2001). Thus, the higher $U(\beta_i)$, the better the quality of the bid. Bidders incurred a cost (c) for each value of x_i submitted. At auction end, the winning bidder received a profit $\pi(\beta_i) = price - c(x_1, x_2)$ where c is the cost incurred for the non-price attribute values submitted in β_i. All non-winning bidders received no profit. To encourage realistic bidding, bidders were informed that if they won the auction, but made a loss, they would be disqualified, and earn zero profits.

To understand bidder perceptions, after each round the simulator asked bidders to indicate on a scale ranging from 0% to 100% their *perceived usefulness* of the information they had received, and their *perceived likelihood of winning* the auction. The simulator controlled the pace of each experiment stage by routing the subjects to a waiting screen until all members of the same group had finished the required tasks of that stage. Consistent with related studies (Bichler 2000, Koppius 2002, Chen-Ritzo *et al*. 2005), a reward mechanism was employed to encourage subjects to bid realistically. At the end of the experiment, the subjects were credited with *show-up* points, and *profit* points made from winning an auction, both of which could be applied towards their course grade. The auctions ran for approximately 55 min.

The next section reports the results of the experiment. Thereafter, inferences are drawn from the findings and their implications are discussed.

5. Results

5.1. *Minimum Information vs. signalling*

To evaluate the first set of hypotheses, i.e. H_{1a}, H_{1b} and H_{1c}, the utility and the perception variables scores of the groups that received signals (treatment groups) to those that received Minimum Information throughout the auction (control group) were compared. Table 1 shows the effects of providing Explicit Preference signals. The results indicate that Explicit Preference signalling yields significantly higher utility scores, higher perceived usefulness of information scores and higher perceived likelihood of winning scores than Minimum Information.

Table 2 shows the means of Utility Score, Winning Probability and Usefulness for individual information elements.

Compared to the control group, Groups 4 and 5 received SOC and Discrete Preference signals respectively during the second stage of the auction. The only additional information that Groups 4 and 5 received over the control group. Therefore, by comparing dependent variable scores of the treatment and control groups measured after the second stage bidding, the effects of SOC and Discrete Preference signals could be examined. In line with the hypotheses both SOC and Discrete Preference signals yielded higher utility, perceived usefulness and perceived likelihood of winning scores than Minimum Information. Therefore, H_{1a}, H_{1b} and H_{1c} are supported.

Interestingly, Table 2 shows that when bidders initially observe the combined effect of Explicit and Discrete Preference signals the perceived likelihood of winning is not different from that of bidders with

Table 1. Effects of explicit preference information.

Dependent variable		N	Explicit Preference Signal Stage 1
Utility score	Control (Group 4,5,6)	72	46.06
	Treatment (Group 1,2,3)	72	64.90
			$t = 7.589$, $p < 0.001$[a]
Perceived usefulness of information	Control (Group 4,5,6)	72	9.83
	Treatment (Group 1,2,3)	72	71.88
			$t = 19.905$, $p < 0.001$
Perceived likelihood of winning	Control (Group 4,5,6)	72	38.15
	Treatment (Group 1,2,3)	72	50.31
			$t = 3.774$, $p < 0.001$

[a]Independent samples t-tests.

Table 2. Means of utility score, winning probability and usefulness for individual information elements.

Dependent variable		N	Discrete preference: Group 2 Stage 2	Discrete preference: Group 5 Stage 2	State of competition: Group 1 Stage 2	State of competition: Group 4 Stage 2	F	Sig.	Tukey's pairwise comparisons
Utility score	Control[a]	24	43.63	43.63	43.63	43.63	10.387	0.001	(1, 4)[c] (1, 5) (2,5)
	Treatment	24	69.15	57.42	78.99	61.94			
			$t = 5.69$, $p < 0.001$[b]	$t = 2.79$, $p = 0.008$	$t = 8.048$, $p < 0.001$	$t = 4.778$, $p < 0.001$			
Perceived usefulness of information	Control	24	12.92	12.92	12.92	12.92	2.324	0.080	
	Treatment	24	71.29	73.04	65.63	57.79			
			$t = 10.11$, $p < 0.001$	$t = 11.67$, $p = .000$	$t = 7.616$, $p < 0.001$	$t = 6.548$, $p < 0.001$			
Perceived likelihood of winning	Control	24	36.54	36.54	36.54	36.54	0.912	0.439	
	Treatment	24	49.21	56.46	58.13	51.38			
			$t = 1.76$, $p = 0.086$	$t = 2.88$, $p = 0.006$	$t = 2.94$, $p = 0.005$	$t = 2.037$, $p = 0.048$			

Note: [a]Control group – Group 6.
[b]Independent samples t-tests.
[c]Tukey's pairwise comparisons, significant at the 0.05 level.

Minimum Information. However, when bidders initially observe a discrete or an explicit signal their perceived likelihood of winning is significantly larger than that of bidders only receiving Minimum Information. This is an interesting finding because it suggests that it is not necessarily true that having a discrete signal or more information will result in a better perception about the likelihood of winning than having Minimum Information. This finding was unexpected so future research may want to explore it in greater detail.

5.2. *Discrete Preference vs. SOC signals*

To test the second set of hypotheses, one-way ANOVA is used to compare the means of the three dependent variables across the treatment groups (Groups 1, 2, 4 and 5). Recall that H_{2a} suggests that bidders with SOC will submit bids with higher utility scores than bidders with Discrete Preference signals, while H_{2b} and H_{2c} indicate that bidders with SOC will perceive such signals to be more useful, and perceive a higher likelihood of winning than bidders with Discrete Preference signals. The results shown in Table 2 indicate that there are no significant differences in utility scores when SOC (Group 4) signals are compared directly to Discrete Preference (Group 5) signals. A significant difference in utility scores between bidders with SOC and bidders with Discrete Preference signals is only detected when bidders with SOC signals also have Explicit Preference (group 1) signals. Moreover, no significant differences in terms of Perceived Usefulness and the Perceived Likelihood of Winning were detected between bidders who received SOC signals and those who received Discrete Preference signals. Therefore, H_{2a}, H_{2b} and H_{2c} are not supported.

5.3. *Revelation policies*

To examine the effects of different revelation policies, the groups that received the same signal combinations were pooled together. One-way ANOVA was then used to test for group differences for each of the dependent variables. Table 3 reports the results. Utility, usefulness of information and perceived likelihood of winning scores differed significantly across the policies. Tukey's pairwise comparisons of the four revelation policies indicate that bidders who received the Full Revelation policy were able to submit bids with higher utility scores ($M = 81.03$, $p < 0.05$) than bidders with the Partial ($M = 68.60$, $p < 0.05$) ($M = 66.53$, $p < 0.05$) or the Minimum Revelation ($M = 55.53$, $p < 0.05$) policy. Bidders receiving the Partial Revelation Policy were able to submit significantly higher bids than those with Minimum Information. Therefore, H_{3a} is supported. In terms of perceptions, the Full Revelation policy was perceived to be more useful ($M = 70.58$, $p < 0.05$) than one of the Partial Revelation policies ($M = 8.63$, $p < 0.05$) and the Minimum Revelation policy ($M = 12.04$, $p < 0.05$). The groups that received partial information (Groups 4 and 5) found the information more useful than those with Minimum Information. Similarly, bidders who received the Full Revelation policy perceived a higher likelihood of winning ($M = 60.92$, $p < 0.05$) than the bidders in one of the groups that received the Partial Revelation policy ($M = 38.04$,

$p < 0.05$) and the group that received Minimum Information ($M = 34.33$, $p < 0.05$). Thus H_{3b} and H_{3c} are partially supported.

5.4. Post hoc analyses

To gain a more thorough understanding of the effects of signals or signal combinations on bidder behaviour, the section below summarises the results of a series of post hoc analyses conducted on (1) the magnitude of the changes in bids invoked by the different signals, (2) the effects of presenting signals in different sequences and (3) the allocative efficiency of the auctions.

5.5. Adjustments in bids induced by signals

The adjustments in bids induced by SOC and Discrete Preference signals were assessed during different stages of the auction. The degree to which bids increased or decreased, when bidders had (1) no prior signals (Groups 4 and 5 at Stage 2), (2) one prior signal (Groups 1 and 2 Stage 2; Groups 4 and 5 Stage 3) and (3) two prior signals (Groups 1 and 2 at Stage 3) were examined. A paired samples t-test was used to test whether the changes were significant. The findings of the analysis are reported in Table 4. Generally, the results indicate that signals spur bidders to improve on previous bids, even when they already have other signals. The only exception to this is Group 4, which received the Discrete Preference signal after they received a SOC signal in prior stages. In this case, the Discrete Preference signal did not spur any significant improvement/change in the bids over the SOC signal. This result is interesting given that for Group 1, the Discrete Preference signal did spur significant improvement/change in bids over the SOC signal. Since the only difference between Groups 1 and 4 is the Explicit Preference signal received by Group 1 during the first stage of the auction, this finding suggests Discrete

Table 3. Means of utility score, winning probability and usefulness for different revelation policies.

Dependent variable	Policy[a]	Mean	Std. deviation	F	Sig.	Tukey's pairwise comparisons
Utility score	1	81.03	12.25	14.342	0.000	(1,2)[b] (1,3) (1,4)(2,4) (3,4)
	2	68.60	16.64			
	3	66.53	14.98			
	4	55.53	24.15			
Perceived usefulness of information	1	70.58	22.12	85.685	0.000	(1,2)(1,4) (2,3)(3,4)
	2	8.63	17.46			
	3	74.46	23.57			
	4	12.04	22.42			
Perceived likelihood of winning	1	60.92	23.11	10.619	0.000	(1,2)(1,4) (2,3)(3,4)
	2	38.04	29.60			
	3	60.46	23.33			
	4	34.33	24.97			

Note: [a]Policy: 1. Full revelation (group 1 & 2); 2. Partial revelation (group 3); 3. Partial revelation (group 4 & 5); 4. Minimum revelation (group 6).
[b]Tukey's pairwise comparisons, significant at the 0.05 level.

Table 4. Bid adjustments induced by SOC and discrete preference signals.

No. of preceding signals	Group	Stage	Mean utility	Std. dev	t	Sig.
0	4	1	47.25	13.48	−6.084	0.000
		2	61.94	12.93		
	5	1	50.43	16.09	−2.247	0.035
		2	57.42	17.12		
1	1	1	66.86	13.29	−3.957	0.001
		2	78.99	13.03		
	2	1	63.90	14.10	−3.032	0.006
		2	69.15	13.73		
1	4	1	61.94	12.93	−0.708	0.486
		2	63.85	15.64		
	5	1	57.42	17.12	−4.116	0.000
		2	69.21	14.10		
2	1	1	78.99	13.03	−2.350	0.028
		2	84.02	12.26		
	2	1	69.15	13.73	−4.480	0.000
		2	78.04	11.74		

Preference signals are only effective in improving bids of over the SOC signals if the bidders are also provided with Explicit Preference signals.

5.6. Sequence effect

It is possible that the sequence in which the treatments are administered (i.e. the order in which the signals are presented to bidders) may impact the bid quality and bidder perceptions. Consequently, we conducted an analysis on the sequence effect in which we compared the groups that received the same signals but in different sequences during the course of the auction. The results of the analysis are reported in Table 5. These results represent the dependent variables means scores for the groups (i.e. Groups 1, 2, 4 and 5) after the third round of bidding. Recall, Treatment Groups 1 and 2 received three identical signals in different sequences. The results of a pairwise comparison using an independent samples *t*-test reveal no significant differences between the two groups in terms of bid-quality, perceived usefulness of information and perceived likelihood of winning. Similarly, Groups 4 and 5 both received the same set of signals in different sequences. No significant differences were detected by the independent samples *t*-test in terms of bid quality between the groups either. There was however a difference in the perceived usefulness and likelihood of winning between Groups 4 and 5 with Group 5 perceiving the information to be more useful and having a higher likelihood of winning than Group 4.

5.7. Efficiency and Pareto optimality

A post hoc analysis was also conducted to evaluate the winner efficiency and Pareto efficiency of the auction. An MRA is considered winner efficient if the most efficient bidder (i.e. the bidder with the lowest cost structure) makes the winning bid (Koppius 2002). An auction outcome is Pareto optimal when there is no other possible bid that can make either the bidder or the bid-taker better off without making the other party worse off (Bichler 2001).

The percentage of efficient and Pareto optimal auction outcomes are shown in Table 6. The results indicate that the groups which received the Full Revelation treatment had the highest proportion of efficient (83%) and Pareto optimal (100%) outcomes while the group that received the Minimum Information treatment has the lowest levels (33%). Among the groups that received Partial Revelation, Group 3 had a higher proportion of Pareto optimal outcomes, suggesting that Explicit Preference information is important for realising Pareto optimal outcomes.

6. Discussion

Research on single attribute auctions has shown that auction outcomes are affected by small differences in information revelation policies (Dufwenberg and Gneezy 2002, Neugebauer and Selten 2006, Mithas and Jones 2007). However, important differences between single attribute and MRA have spurred researchers to call for work examining the 'consequences of different information revelation and support policies' on both bid-takers and bidders in multi-attribute auctions (Teich *et al*. 2006). This study takes up this challenge and offers empirical insights into the potential ramifications of employing different information revelation policies in MRA.

The results of our experiment are largely consistent with the theoretical arguments presented. They reveal that information asymmetry between bid-takers and bidders can result in poor performing auctions. By reducing the level of information asymmetry in MRA through signalling, bid-takers can enable bidders to submit higher quality bids. Generally, bidders find

Table 5. Sequence effect.[a]

Dependent variable	Group	Mean	Std. deviation	t	Sig.
Utility score	1	84.02	12.26	1.727	0.091
	2	78.04	11.74		
Perceived usefulness of information	1	65.50	24.18	−1.620	0.112
	2	75.67	19.01		
Perceived likelihood of winning	1	58.92	23.91	−0.596	0.554
	2	62.92	22.60		
Utility score	4	63.85	15.64	−1.248	0.218
	5	69.21	14.10		
Perceived usefulness of information	4	66.71	27.12	−2.389	0.021
	5	82.21	16.56		
Perceived likelihood of winning	4	50.13	19.05	−3.395	0.001
	5	70.79	22.94		

Note: [a]Pairwise comparisons conducted using independent samples *t*-test.

Table 6. Percentage of efficient and Pareto optimal auctions.

	Performance	
	Efficiency (%)	Pareto optimality (%)
Treatment		
Full revelation	83	100
Partial revelation[1]	58	50
Partial revalation[2]	33	83
Minimum revelation	33	33

Note: Partial revelation[1] – Groups 4 and 5.
Partial revelation[2] – Group 3.

signals *useful* and their *perceived likelihood of winning* is also positively impacted. Understanding bidder perceptions is essential as this may impact the level of performance in subsequent rounds or future auctions. These results are consistent with similar experimental studies, which suggest that information plays an important role in determining the performance of MRA (Koppius 2002, Teich *et al*. 2004, Bichler and Kalagnanam 2005). Most MRA research often does not consider the ramifications of adopting different information revelation policies. However, in light of our findings, it is evident that information revelation policies should be an integral component of MRA design.

With regard to the individual types of signal considered, from the results we learn that *Explicit Preference* signals are essential for enabling bidders to submit high quality bids. Furthermore, when Explicit Preference signals are combined with other types of signals, better quality bids can be realised. When bidders are provided with both Explicit Preference and *SOC* signals, they submit higher quality bids than when they only have an SOC signal. This result has important practical implications, particularly to multistage MRA with a hard closing rule where bid-takers choose to reveal different information at different stages. Bid-takers often voice concerns about revealing their utility functions to bidders due to fears of bidders shifting all the gain of trade to themselves (Strecker and Steifert 2003). However, this finding suggests that they can trigger significantly higher quality bids by revealing their utility function. In a recent study Strecker and Steifert (2003) observed similar outcomes and concluded that when Explicit Preference signals are not provided to bidders, bidding tends to be 'an unguided explorative process in which bidders are assumed to apply an ad hoc, trial-and-error strategy, and which is less likely to lead to efficient outcomes than in the case where the buyer reveals her preferences'. During our debriefing sessions, many of the subjects who did not receive Explicit Preference signals indicated that bid construction was 'difficult and frustrating' since they were uncertain about the preferences of the bid-taker. Even those with SOC and Discrete Preference (Groups 4 and 5) signals indicated that bidding would have been less difficult if they knew the bid-taker's preferences. Thus, designers of MRA should not neglect the importance of Explicit Preference signal revelation, as difficulty and uncertainty with a mechanism could have dire consequences on both the quality of bids submitted during the auction and bidder participation in future auctions.

When the effects of SOC and Discrete Preference signals were compared, the results revealed that SOC signals might not necessarily translate into better quality bids for bid-takers than Discrete Preference signals. While this was unexpected given that SOC signals provide bidders with more information than Discrete Preference signals, one plausible explanation for this finding lies in bidders' reactions to each signal type. Close analysis of the data revealed that when bidders observed SOC signals their subsequent bid was anchored by the top-ranked bid. In an attempt to win the auction, bidders focused on making improvements to the top-ranked bid. However, as they also wanted to profit from the transaction they only made marginal improvements to the top-ranked bid. It is important to note that the quality of the top-ranked bids varied randomly from low to high. Therefore, the aggregate impact of SOC signals was an improvement in the bid quality compared to when there is Minimum Information, but it fell short of meeting the the bid-taker's exact preferences. The impact of Discrete Preference signals was similar. When bidders received Discrete Preference signals, they reacted by making only marginal improvements to their prior bid. Discrete Preference signals in our study only suggest the attribute, but not its magnitude, that could improve bid quality. In most cases, when bidders observed this signal, to maximise their profits, they only made marginal adjustments to the price, and to the attribute specified in the signal. Thus, while Discrete Preference signals improved bid quality, it fell short of meeting the bid-taker's exact preferences. To summarise, SOC and Discrete Preference signals in this study elicited similar reaction from bidders that resulted in similar auction outcomes. While SOC signals provide more information, they did not necessarily translate into better bids compared to Discrete Preference signals. The implications of this finding are important for both practitioners and researchers. While SOC signals are very popular among bid-takers, primarily because it is believed that they can stimulate aggressive bidding, a major disadvantage of SOC signals for bid-takers is that they can reveal too much information that may result in bidder collusion (Varma 2000). In this study we found that Discrete Preference signals are a viable alternative to SOC signals. In fact there was no detectable difference in the utility scores when bidders had SOC or Discrete Preference signals. Additionally, bidders found each signal type equally useful, and they perceived an equal probability of winning the auction. For practitioners who are reluctant to use SOC signals due to fears of bidder collusion (Varma 2000), our results indicate that it is possible to use Discrete Preference signals to realise comparable levels of MRA performance. The advantage of Discrete Preference signals is that information about competing bidders is not revealed, thus the possibility of bidder collusion during the auction is minimised. Also, bidders sometimes fear partaking in auctions that reveal their bids as competitors may learn their threshold values and bidding strategies over time and use this information against them in future auctions or transactions. Discrete Preference signals can mitigate such concerns, thus bidders are also likely to find a Discrete Preference signal revelation approach more appealing. An opportunity this finding presents for researchers relates to whether Discrete Preference signals that provide bidders with greater detail of how to improve on a previously placed bid (e.g. the signal employed by Chen-Ritzo *et al.* 2005) fare against SOC and Explicit Preference signals. Such insights could help improve the design of MRA.

7. Conclusion, limitations and future research

This study demonstrates through laboratory experiments how certain information asymmetries between bid-takers and bidders can result in poor bid selection and ultimately poor auction performance. It also discusses bidders' perceptions on information usefulness as well as the impact on their level of confidence when exposed to various pieces and streams of information.

Despite these contributions, there exist limitations which future research can address. For instance, the context, subjects and structural factors used in the study constrain the generalisability of the results. Although it is preferable for the experiments to be conducted in a context-free setting, a setting familiar to our subjects was selected in order to minimise the cognitive complexity associated with dealing with an unfamiliar context and an unfamiliar complex auction mechanism (Koppius 2002). Perhaps, future research can look into running the same experiments under different contexts or in a context-free setting.

Future work can also consider different types of subjects. The subjects in this study primarily consisted of undergraduate students from a single academic institution. Although these students were well versed with electronic auctions and electronic commerce, it would be desirable for future studies to replicate this study using subjects from different institutions or using non-student samples. For instance, procurement professionals may be used. Although the application of multi-attribute auctions is not limited to the procurement domain, they are likely to be used in such settings. Therefore, it would be interesting to observe whether professional bidders working in procurement departments would behave in a similar manner when they are exposed to the same information elements as student subjects.

Additionally, since the intention of this study is to examine bidders' initial reactions to information that they observe, the structural factors (auction design) in the study were kept constant, i.e. MRAs with four bidders, three attributes and three stages were considered. While the above results do provide some important insights into the response of MRA bidders to different signals, it should be noted that variations in the design of the auction mechanism may yield different results. For instance, if a soft rather than a hard closing rule had been adopted or number of bidders, the number of attributes or the number of rounds are changed the bidders could have adopted a different bidding strategies that could ultimately result in different auction outcomes. Therefore, future studies will have to evaluate whether or not the current findings are applicable to MRA that differ in structure.

Finally, while this study evaluated two perception measures, i.e. the perceived likelihood of winning and the perceived usefulness of information, other perception measures such as perceived fairness of the auction may need to be considered (Pekeč and Rothkopf 2003). Future studies may wish to explore whether perceived fairness in MRA influences the quality of bids submitted as this could provide additional insights for bid-takers on how they should design effective and efficient MRAs.

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