

DECISION SUPPORT IN MULTI-ATTRIBUTE REVERSE AUCTIONS

Kholekile L. Gwebu
Department of Decision Sciences
Whittemore School of Business and Economics
University of New Hampshire
Durham, NH 03824
khole.gwebu@unh.edu

ABSTRACT

This study seeks to better understand bidding decision support in multi-attribute reverse auctions. It views bidding as a decision making process and attempts to determine how tools that aid different stages of the decision making process affect the quality of the bids submitted. Two experiments reveal that decision support tools that impact all the stages of a bidder's decision making process can generate high quality bids. However, the findings also reveal that even with such tools, variations in auction structural elements such as the number of bidders and the number of auction attributes can impact the quality of the bids submitted.

Keywords: bid-quality, decision-making process, decision support, multi-attribute auctions

1. Background

Reverse auctions are market mechanisms that enable sellers rather than buyers to compete via a bidding process in order to supply goods or services [Dans, 2002]. While the importance of providing bidders with adequate decision support in reverse auctions has been stressed [Leskelä, Teich, Wallenius, Wallenius, 2007], it has not been a mainstream concern in the literature [Teich, Wallenius, Wallenius, Koppius, 2004]. Recently some scholars have called for more research on ways to better support bidder decision making. For instance Leskelä et al. [2007] state that it is imperative for auctioneers to provide decision support for the bidders in combinatorial reverse auctions. Teich, Wallenius, Wallenius, and Zaitsev [2006] suggest that well designed auctions should not only provide support for bid-takers, but they should also enable bidders to make good bids. Rothkopf and Whinston [2007] express that studies which consider the decision support potential of feedback information in reverse auctions would be an important extension to auction literature. In response to this call, this study focuses on decision support in the context of multi-attribute reverse auctions. Drawing on Simon's [1960] decision making model, this study views bidding as a decision making process, and investigates the effects of various decision support tools on the different stages of a bidder's decision making process and ultimately their impact on the quality of bids submitted. Bid quality refers to the desirability of a bid to a bid-taker; the more desirable the bid the better its quality.

This study is motivated by both a basic need and a fundamental desire to develop a systematic approach which ensures that decision support tools developed for a complex auction can yield high-quality bids. Currently, this approach is lacking. The few existing studies on decision support in reverse auctions have concentrated on developing different *types* of tools to assist bidders during the bidding process. Some have focused on creating mechanisms that minimize the time and effort involved in bidding by automating the bidding process through the development of intelligent software agents [Yung, Yang, Lau, Yen, 2000]. For instance, in "price only" business-to-consumer (B2C) and consumer-to-consumer (C2C) auctions, artificial sniper agents have been designed to place bids seconds before the auction closes on behalf of bidders. In some cases sniping agents have been found to be as effective as humans at placing bids [Bapna, 2003] and their use is becoming more common in practice [Ku and Malhotra, 2001]. Examples of sniping agents used in B2C and C2C auctions include EZ Sniper, JustSnipe, JBidwatcher just to name a few. Software agents have also been employed in reverse auction mechanisms. For example, to automate bidding in procurement reverse auctions, Sikora and Sachdev [2008] create a tool that facilitates the use of artificial agents to learn competitors' strategies and then propose effective responses during the bidding process.

Other studies have focused on reducing bidder's cognitive strain through creating tools that provide computational support or feedback information. For instance, Gallien and Wein [2005] construct a mechanism to assist bidders determine the bids that will maximize their potential payoff in a subsequent auction round. The mechanism allows bidders to enter their production cost into the tool which then computes bids and presents competitive bid information as feedback for decision support. In a related study, Leskelä et al. [2007] build a decision support tool for combinatorial auctions that assists bidders by generating a shortlist of price-quality

combinations which would be acceptable to the bid-taker. Bidders can then use the short list to select their bid i.e. the most preferred price-quantity combination. Adomavicius and Gupta [2005] develop and implement data structures and algorithms into a tool that provides comprehensive real-time information about the state of the auction to support bidders' evaluation of bids and bidding strategies. They evaluate their tool through an experiment. The results indicate that the tool is able to provide "real-time bidder support for auction sizes where even a single-time winner determination problem is considered challenging" [p 171]. Teich, Wallenius and Wallenius [1999] also developed a tool to provide bidders with auction status information, but in a multi-unit multi-attribute auction. The tool discloses the status of a bid as either being active, semi-active or inactive. An active bid would be accepted in its entirety by the bid-taker if the auction were to close at that moment, a semi-active bid would be partially acceptable (i.e. the bidder receives partial quantity) to the bid-taker, and an inactive bid would be totally unacceptable to the bid-taker because other superior bids exist. Based on these states a bidder selects their next course of action.

Although all the above mentioned studies create tools that provide some form of decision support capabilities for bidders, the literature is yet to propose a systematic approach which evaluates and ensures that decision support tools developed for reverse auctions indeed sufficiently and effectively support bidding. Without such a systematic approach, it is highly likely that tools developed are only able to provide limited decision support because they may focus on certain aspects of decision making e.g. computation or bid-automation, but not others. This lack of a systematic approach could also hamper efforts to develop a solid basis for decision support design for reverse auctions. Hence, the focus of this study is not to develop a new decision support tool. Rather, it utilizes Simon's [1960] decision making model and theoretically maps the bidding process in a complex auction onto Simon's three decision-phase framework. It then investigates, both theoretically and empirically, the importance of DSS tools supporting all three phases of bidder decision making in order to assist submission of quality bids in reverse auctions. By adopting a process perspective, this study demonstrates that Simon's [1960] decision phase framework serves as a potent lens to systematically evaluate the extent to which a decision support tool assists bidding in complex auctions. A process perspective will permit us to decompose the bidding process then trace through its different components to gain a better understanding of how decision support tools should be designed to facilitate effective bidding. Only then can we begin to provide systematic recommendations on generic features that a decision support tool must possess in order to provide ample decision support capabilities to bidders in complex auctions. To control the scope of this study the case of a single type of reverse auction mechanism that has become very popular [Bichler and Kalaganam, 2005], the multi-attribute reverse auction, will be considered.

The remainder of the paper is structured as follows. The next section proposes a set of hypotheses on the relationship between the decision making process, decision support, and bid quality. Thereafter, the hypotheses are tested through a series of experiments, and then the implications of the findings are discussed. Finally, the limitations of the study and directions for future research will be presented.

2. The Decision Making Process in Multi-attribute Reverse Auctions

Put simply, bidding is a decision making process in a competitive environment constrained by rules and procedures. While there are only a few studies that focus on how bidders make decisions in reverse auction environments, there is a considerable body of work which considers human decision making processes in general. A key theorem which has emerged from this work is the Phase Theorem. The following section discusses the relationship between the Phase Theorem and bidding in multi-attribute reverse auctions.

The Phase Theorem suggests that decision making is a *process* that consists of *multiple* distinct yet related phases. Over the years it has been successfully applied to a variety of domains ranging from abstract mathematical problem solving at the individual level [Polya, 1957] to applications in real world problem solving at the organization level [Kast and Rosenzweig, 1979]. In the Information Systems domain alone, it has been used when studying the impact of e-commerce channel decision support capabilities on the consumer's decision-making process [Kohli, Devaraj, and Mahmood, 2004], the influence of management support systems on the process and outcomes of health care decision making [Forgionne and Kohli, 1995], and the benefits of decision-oriented information systems [Vetschera and Walterscheid, 1995] just to name a few.

While, the Phase Theorem is generally accepted and dominates the literature on problem-solving, the number of phases used in prior studies has varied [Lipshitz and Bar-ILan, 1996]. For instance, a model proposed by Brim et. al [1962] consists of five phases, namely, identifying the problem, obtaining relevant information, generating potential solutions to the problem, selecting a strategy for a course of action, and performing the action. On the other hand, Polya's [1957] model consists of only three phases: understanding the problem, devising a plan, and carrying out the plan and reflecting on the plan. Lipchitz and Bar-ILan [1996] conducted an analysis of different phase models and concluded that "different phase models overlap to the extent that they can be roughly mapped onto one another even

when they differ in their number of phases and terminology.” Thus, the general consensus is that decision making is a process with several stages even though the number of stages and terminologies vary across different models of decision making process.

To gain a better understanding of the bidding process in multi-attribute reverse auctions Simon’s [1960] decision process model is employed. This model is arguably the most widely used and accepted human decision making process model [Forgionne and Kohli, 1995; Forgionne, 2000] and it is general enough to cover the major activities involved in decision making. The model suggests that decision makers follow three phases in their decision-making process: an *intelligence* phase, a *design* phase, and a *choice* phase. Failure to effectively engage in any one of the phases will result in sub-optimal solutions [Bolloju, et al 2002]

In a multi-attribute reverse auction, a buyer (bid-taker) offers a contract for the supply of specific goods or services. The auction process typically begins with a request for quotation (RFQ) describing the buyer's specific requirements which may include such information as auction protocol, the goods or services and the attributes the buyer is interested in, and buyer’s preferences. Qualified suppliers who intend to participate in the bidding need to collect such information in order to submit bids that meet the requirements of the bid taker. During the auction they would also benefit from receiving information such as competing bids, ranking of the competing bids, and bid taker’s on-going feedback on how they can improve on their bids since they not only need to submit bids that satisfy bid-taker’s requirements, but also need to outbid the competitors. Based on the information collected, they generate a set of potential bids, evaluate the bids, and then choose the optimal one for submission. This process in essence, is a decision making process. Hence activities in multi-attribute reverse auction bidding can be mapped onto Simon’s [1960] decision process model. During the intelligence phase the decision maker recognizes the problem at hand and attempts to acquire the necessary quantitative and qualitative data to address it [Kwon, 2006; Forgionne, 2000]. In a multi-attribute reverse auction, information such as the auction rules and procedures, the attributes on which to bid, as well as the relative importance of each attribute to the bid-taker helps bidders understand the problem (how to bid, what attributes to bid on, and what the bid-taker prefers). A well designed decision support system in a multi-attribute auction should therefore provide the appropriate means to allow bidders to gather such quantitative and qualitative information.

Once the decision maker has collected the necessary information to understand and address the problem, they engage in the design phase of the decision making process. According to Simon [1960] the design phase entails the generation and evaluation of alternative solutions to the problem. In multi-attribute reverse auctions bidders must generate and evaluate a set of bids that will enable them to best achieve their auction objectives. Information such as competitors’ bids, bid ranking, the current status of existing bids, bid-taker’s recommendation on how to improve on previous bids can help bidders generate and evaluate alternatives bids. Accordingly, well-designed decision support tool that provides such assistance and information should contribute positively to a bidder’s decision making process.

Finally, during the choice phase, decision makers select one of the alternatives. In a multi-attribute reverse auction this stage of the decision making process entails selecting a bid from one of the bid alternatives generated during the design phase. If this stage of the decision making process is adequately supported a bidder should be able to easily and quickly identify and select a bid that maximizes his or her chance of winning the auction by satisfying the bid-taker’s bid preference and outbidding the competitors. Computational tools for determining profit differences between alternative bids can help bidders select their bid.

Many studies have focused on developing tools that only impact part rather than the entire decision making process (See Table 1).

Based on decision support tools used in prior studies, this paper seeks to determine the relationship between the quality of bids received by the bid-taker and three varying levels of decision support: Extensive Decision Support (EDS), Partial Decision Support (PDS) and Limited Decision Support (LDS). EDS refers to situations where support is provided for all three phases of the decision making process (e.g. Chen-Ritzo, Harrison, Kwasnica, and Thomas [2005];Koppius [2002]) while PDS supports some but not all phases of the decision making process (e.g. Teich, Wallenius, Wallenius, and Zaitsev [2006] ;Bichler [2000] ;Strecker and Seifert [2004]), and LDS does not support any of the phases to the same degree as EDS or PDS. One of the primary motivations behind the development of decision support systems is that appropriate support should be provided in every phase of the decision process to ensure effective decision making [Sprague et al., 1982; Carlson, 1978; Bolloju, 2002; Kivijarvi et al., 1999]. It is hence expected that the bid-taker will receive better quality bids if more phases of the decision making process are supported:

H₁. Using EDS will result in better quality bids than using PDS or LDS.

H₂. Using PDS will result in better quality bids than using LDS.

While the level of decision support adopted will play an important role, it may be possible that even if bidders have extensive decision support, various auction structural elements can also impact bid quality. If structural elements impact the quality of bids even when all the phases of the decision making process are supported, bid-takers need to be cognizant of this and take it into consideration when designing their auctions.

Table 1: Decision Support Tools in Multi-attribute Auction Studies

| Study | Decision Support | Phases of Decision Making Process Most Impacted |
|---|---|---|
| Teich, Wallenius, Wallenius, and Zaitsev [2006] | Suggested price Bid Status | Intelligence Design |
| Chen-Ritzo, Harrison, Kwasnica, and Thomas [2005] | Bid taker's preferences Current best bid and bid status Calculation tool | Intelligence Design Choice |
| Strecker and Seifert [2004] | Buyer's preferences Calculation tool | Intelligence Choice |
| Koppius [2002] | Bid taker's preferences State of competition Relative score of each bid Calculation tool | Intelligence Design Design Choice |
| Strecker [2003] | Bid taker's preferences Calculation tool | Intelligence Choice |
| Teich, Wallenius, Wallenius, and Zaitsev [2001] | Bid taker's preferences Bid Status | Intelligence Design |
| Bichler [2000] | Buyer's preferences Calculation tool | Intelligence Choice |
| Teich, Wallenius and Wallenius [1999] | Reservation prices Bid Status Minimum bid increment required | Intelligence Design Design |

3. Auction Structure

Structural elements of auctions may contribute to bidding complexity. Structure elements include but are not limited to the number of bidders in an auction, the number of attributes, the number of units auctioned, and the number of auction rounds. This study will only consider single unit multi-attribute auctions such as those that would be conducted to procure a supercomputer. Single unit multi-attribute auctions are used in practice and have often been considered in prior literature (e.g. Beil and Wein [2003]; Chen-Ritzo, Harrison, Kwasnica, Thomas [2005]; Strecker and Seifert [2004]). Future studies may wish to examine combinatory multi-attribute reverse auctions. The structural elements of interest here are those which have not received significant attention in prior multi-attribute auction studies i.e. the number of attributes and the number of bidders. Prior studies have not found a significant relationship between the number of auction rounds and multi-attribute auction performance [Koppius, 2002], thus auction rounds will not be considered.

3.1. Number of Attributes

Varying the number of attributes on which bidders can submit bids can complicate the bidding process because it changes the potential number of bids that bidders can select. If the number of attributes increases, the number of alternative bid options that a bidder needs to evaluate can increase significantly. Consider the simple example depicted in Table 2 which illustrates this point.

Table 2: Illustrative Example of the Effect of Varying the Number of Attributes

| Auction Scenario | Number of discrete bid values for each attribute – (D) | Number of attributes – (A) | Potential number of bids – (D ^A) |
|------------------|--|----------------------------|--|
| 1 | 5 | 2 | 25 |
| 2 | 5 | 3 | 125 |
| 3 | 5 | 4 | 625 |

Three different auction scenarios are shown in the example. The number of bid values for each attribute is discrete and constant. The only variable is the number of attributes. Note that a small increase in the number of attributes increases the number of alternative bids exponentially. In the first scenario bidders need to evaluate 25 different bid alternatives. With adequate decision support, they should be able to do so relatively easily. However, in the third scenario the bid space increases significantly to 625 alternative bids and evaluation of each alternative would take more cognitive effort. Extant research suggests that when confronted with a large number of alternatives, in order to simplify the decision making process, decision makers tend to first employ a non compensatory strategy to eliminate unacceptable alternatives and then employ a compensatory strategy to evaluate the remaining alternatives [Lussier and Olshavsky, 1979]. However, in auctions with inadequate decision support bidders may not even be able to determine which alternatives are unacceptable, thus the decision making process remains complex and may result in suboptimal outcomes. To encapsulate, even though provision of decision support in a multi-attribute auction tends to make the decision making process less complicated compared to no decision support, an increase in the number of attributes will result in an increase in decision complexity due to the significant increase in the bid space. The quality of the bids submitted may in turn suffer due to the increase in complexity. Therefore:

H₃. Increasing the number of attributes in a multi-attribute auction will have a negative effect on bid quality.

3.2. Number of Bidders

The second dimension of complexity considered in this study is the number of bidders. Auction literature holds two conflicting views on the effects of varying the number of bidders. One stream of research has suggested that increasing the number of bidders can yield better quality bids for bid-takers [Gaver and Zimmerman, 1977; Brannman, Klein, and Weiss, 1984; Bulow and Klemperer 1996]. Generally, this body of literature argues that a large number of bidders stimulates competition and ultimately improves the quality of bids for the bid-taker. However, the other stream of research, has argued that there are benefits to having fewer participants competing in an auction as fewer bidders mean that bidders will perceive a higher chance of winning and will hence be more inclined to compete aggressively [Harstad, 1990; Hall 1998]. Moreover, some have suggested that beyond a certain point increasing the number of bidders can have a negative effect on auction outcomes. For instance, Millet et al. [2004] state that “bidding momentum may be lost when suppliers realize they are competing against a large number of bidders.” Finally, research that examines how decision makers react in competitive situations when the number of potential rivals increases has found a negatively relationship between the number of rivals and the decision process and outcomes [Klemz and Gruca, 2003]. This body of literature argues that when a decision maker is confronted with multiple rivals they evaluate each rival’s strategy before formulating their own response. The more rivals involved, the more effort and time required to evaluate each rival’s strategy then formulate a counter strategy. Oftentimes in such situations decision makers employ non compensatory decision making processes which result in suboptimal decisions. Given the complexity of multi-attribute auctions, an increase in the number of bidders seems highly likely to place tremendous cognitive strain on bidders to identify a high-quality bid. Based on these arguments it stands to reason that,

H₄. Increasing the number bidders in a multi-attribute auction will have a negative effect on bid quality.

The next section describes the experiments conducted to understand the relationship between the decision making process, auction structure and bid quality in multi-attribute reverse auctions.

4. Methodology

Two experiments were conducted to assess the hypotheses. The first experiment examined H₁ and H₂ and the second experiment examined H₃ and H₄.

4.1. Experiment 1: Decision Support and the Decision Making Process

The first experiment was designed to test the relationship between the decision making process, decision support, and the quality of bids received by the bid-taker. Participants received one of three levels of decision support EDS, PDS, or LDS. They then evaluated the extent to which they perceived the DSS to influence the different phases of their decision making process on an instrument with a seven point Likert scale. Participants also submitted multi-dimensional bids (i.e. bids on multiple attributes) which were evaluated by the bid-taker.

4.1.1. Instrument validity and reliability

The instrument used to assess the impact of the level of decision support on the stages of the decision making process was adapted from Kohli, Devaraj and Mahmood [2004]. The instrument consisted of 8 items which measured the three different dimensions of the decision making process i.e. intelligence, design and choice. The subjects responded to each of the questions on the instrument (shown in Table 4) on a Likert scale that ranged from strongly disagree (scored 0) to strongly agree (scored 7). To be useful, it is important for an instrument to demonstrate convergent and divergent validity [Nunnally and Bernstein, 1994]. To assess the convergent and divergent validity, confirmatory factor analysis with Varimax rotation was performed. Before proceeding with the

factor analysis, it was necessary to assess the sampling adequacy. This was done using the Kaiser-Meyer-Olkin (KMO) and Bartlett's test for Sphericity. Acceptable levels of KMO are 0.5 and above [Dziuban and Shirkey, 1974] and the level of significance of the Bartlett's test for Sphericity should be significant at the 0.05 level [Hair, Black, Tatham and Anderson, 1998]. Table 3 shows that the results of the tests meet acceptable levels that permit proceeding with the factor analysis.

Table 3: Kaiser-Meyer-Olkin [KMO] and Bartlett's test for Sphericity.

| Construct | KMO | Bartlett's test (Sig.) |
|--------------|------|------------------------|
| Intelligence | 0.72 | <0.001 |
| Design | 0.50 | <0.001 |
| Choice | 0.50 | <0.001 |

The Scree test criterion [Hair et al. 1998] suggested the existence of three factors. The eigenvalues showed that the first factor explained 50.59%, the second factor 18.05%, and the third factor 14.23% of the variance. Collectively these three factors explained over 82% of the variance. The results from the rotated component matrix (Table 4) show that there are no cross loadings above 0.37. Cronbach's Alpha was used to assess the reliability of the instrument. Generally the lower limit for Cronbach's Alpha should be 0.7 [Hair et al. 1998; Robinson, Shaver, and Wrightsman, 1991]. The results show alphas of 0.87, 0.84, and 0.72 for the intelligence, design and choice components respectively.

Table 4: Instrument Validity and Reliability, Rotated Component Matrix^a

| Item | Component | | |
|--|--------------|--------|--------|
| | Intelligence | Choice | Design |
| The information provided made it easy to determine the relative importance of Memory size to the buyer | .918 | .129 | .188 |
| The information provided made it easy to determine the relative importance of Hard Drive size to the buyer | .849 | .242 | .099 |
| The information provided made it easy to determine the relative importance of Price to the buyer | .802 | .129 | .251 |
| Selection of the bids submitted did not take a long time | .095 | .918 | .178 |
| It was easy to pick the best bids from alternative bids | .303 | .866 | .090 |
| The information provided made it possible to identify various alternative bid combinations | .332 | -.022 | .848 |
| The information provides made it easy to evaluate various bid alternatives | .093 | .365 | .829 |
| Cronbach's Alpha | 0.869 | 0.840 | 0.717 |

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

4.1.2. Scenario

The scenario chosen for the experiments is one that was considered realistic and uncomplicated for the subjects to understand. It involves a situation where a single bid-taker/buyer [represented by a computer program] who wants to procure a computer [in practice this may be supercomputer] from one of four bidders [human subjects]. The bid-taker derives satisfaction from a combination of three negotiable attributes, Hard-drive [x_1], Memory [x_2], and Price [x_3]. Consistent with prior work [Bichler, 2000] bid quality, operationalized with bid-taker utility, was determined using the following function:

$$U[B_i] = \sum_{i=1}^p w_i S(x_i) \tag{1}$$

where $U[B_i]$ is the utility derived by the bid-taker from bid i and w_i is the weight of importance assigned to attribute x_i by the bid-taker. $S[x_i]$, computed using function 2, represents the scoring function used to assess the distance between the bid value submitted by a bidder for attribute x_i and the bid-taker's desired value for that attribute:

$$S[x_i] = \frac{x_i - x_{worst}}{x_{best} - x_{worst}} \quad [2]$$

where x_{worst} represents the bid-taker's least desired value for attribute x_i and x_{best} is bid-taker's most desired value for x_i . To make the auction realistic all the bidders received cost schedules which showed them the costs they would incur [Bichler, 2000] for various attribute value combinations i.e. each bid. All costs were directly associated with the reward mechanism [extra credit points] such that the higher the cost the bidder incurred for a particular bid, the fewer extra credit points received if (s)he won the auction. Thus, bidders attempted to win the auction while minimizing the cost incurred for a bid.

4.1.3. Method

The experiment was conducted in a computer laboratory using a web based multi-attribute auction application. The screen of the application consisted of three regions, namely a bid input region, a decision support region, and a computation region. The bid input region included sliders for each of the attributes under consideration. Such that for the three attribute auction there were three sliders; one for hard-drive value inputs [x_1] [in Gigabytes ranging from 0 to 100] another for memory value inputs [x_2] (in Megabytes ranging from 0 to 500) and one for price inputs [x_3] (in US\$ ranging from 0 to 600). To bid subjects simply dragged each slider to the desired value. The decision support region displayed either EDS or PDS or LDS depending on the bidder's treatment group. Finally, the computation region had an embedded tool that permitted bidders to calculate how much profit they could make from a bid that they had selected in the input region if that bid won the auction. Once satisfied with a bid, bidders clicked on a submit bid button which sent the selected bids to the bid-taker (computer program) which evaluated the bids using function 1.

One hundred and twenty undergraduate students from a large Midwestern university participated in the first experiment. Consistent with the protocol used in related studies [Koppius, 2002; Strecker and Seifert, 2003; Strecker and Seifert, 2004], upon arrival at the lab subjects were trained then randomly seated at visually isolated computer terminals. Training comprised of a presentation that provided a detailed description of the scenario, auction simulator, and auction rules and procedures. Subjects were randomly assigned to one of the three treatment groups such that the group that received EDS had 48 bidders, the group that received PDS had 48 bidders and the group that received LDS had 24 subjects. Within each treatment group bidders competed with three other bidders. In terms of decision support, bidders in the EDS treatment group received information on the bid-taker's weighting of each of the attributes, information on competitors' bids, bid rankings and recommendations on how to make improvements on a previously placed bid and, the calculation tool that allowed bidders to compute the profit they would receive from the selected attribute combinations. The first piece of information is geared toward supporting the intelligence phase of the decision making process while the second piece of information was geared towards supporting the design phase. The calculation tool supports the choice phase. Therefore EDS provided support for all three phases of bid decision making process. Bidders in the PDS treatment group received information on competitors' bids, bid rankings and recommendations on how to make improvements over a previously placed bid and the calculation tool. Thus, it is expected that the intelligence phase of the decision making process should not be adequately supported for bidders with the support of PDS while the design and choice phases should be. Finally the LDS treatment group was only provided with the calculation tool and information on the auction rules and procedures which the other two groups also received. This is the minimum amount of information required to conduct a complex auction like multi-attribute reverse auction and such information may not make a significant contribution to any of the phases of the decision making process.

4.1.4. Manipulation check

A manipulation check determined whether bidders recognized and used the decision support provided to them. All the subjects were asked to state on a scale from 0 to 100 how useful the decision support they had been provided with was. If the manipulation was effective groups receiving EDS should have the highest perceived usefulness scores, followed by groups receiving PDS and LDS respectively. One-way analysis of variance (ANOVA) with Bonferroni adjustment was used to compare the mean scores of perceived usefulness for the three groups. Consistent with expectations EDS (M=69.44, SD= 15.98) was perceived to be significantly ($p < 0.05$) more useful than PDS (M=49.76, SD=15.46) and LDS (M=11.87, SD=20.43). PDS was perceived to be significantly ($p < 0.05$) more useful than LDS.

4.1.5. Results

During the auction bidders submitted bids and answered a set of questions (see Table 4) which assessed the extent to which they perceived the decision support provided to them as facilitating the intelligence, design, and choice phases of the decision making process. One way ANOVA was used to test H_1 and H_2 which propose that the greater the level of support for the bid decision making process, the better quality of bids. Given that the bids within

a group of competing bidders may influence each other and consequently result in observations not being independent analysis was conducted at the group level. The average bid from each group rather than individual bids was used as the unit of analysis. Differences were considered significant at $p < 0.05$. Figure 1 illustrates the results of the impact of different types of decision support on different phases of the decision making process while Figure 2 illustrates the results of the impact of different types of decision support on bid quality.

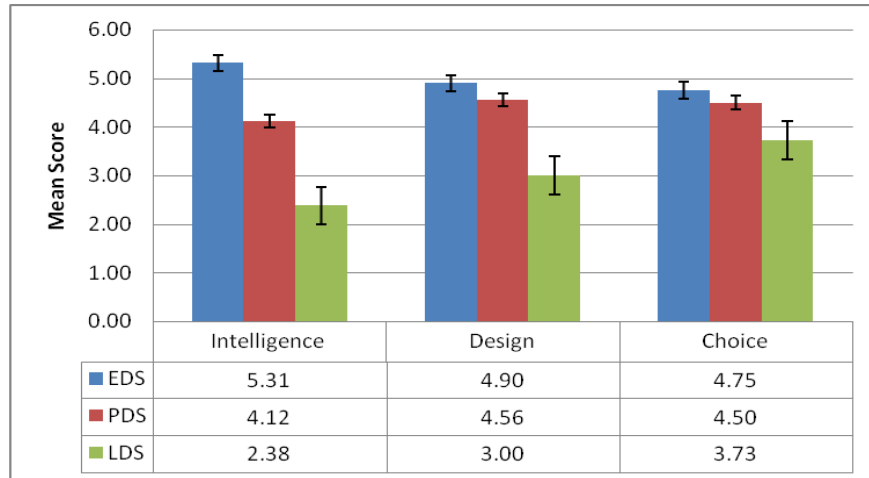


Figure 1: Impact of different types of decision support on different phases of the decision making process

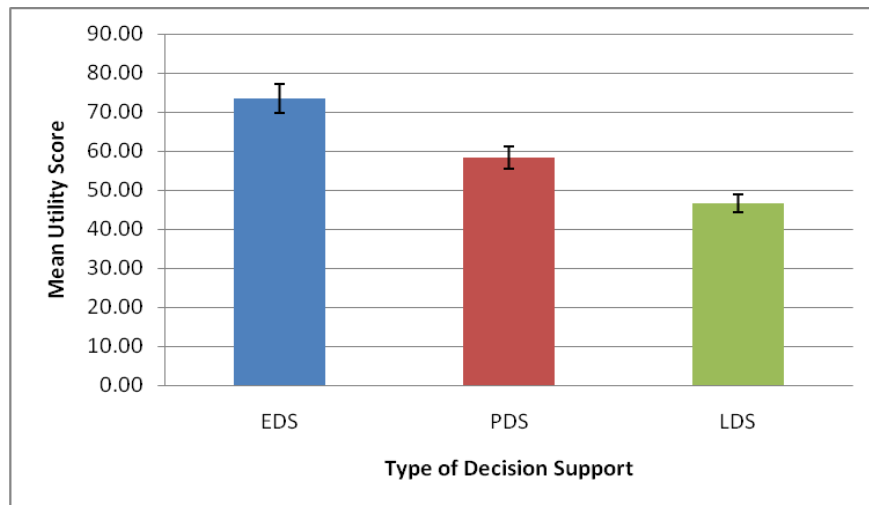


Figure 2: Impact of different types of decision support on bid quality

Table 5: Results - ANOVA and Pairwise comparisons

| DSS \ Variable | EDS | PDS | LDS | F | p-value | Pairwise comparison-significant mean differences* |
|----------------|-------|-------|-------|-------|---------|---|
| Intelligence | 5.31 | 4.12 | 2.38 | 39.69 | <0.001 | [1,2] [1,3] [2, 3] |
| Design | 4.90 | 4.56 | 3.00 | 11.30 | <0.001 | [1,3][2, 3] |
| Choice | 4.75 | 4.49 | 3.73 | 6.61 | 0.005 | [1,3][2, 3] |
| Utility | 73.49 | 58.35 | 46.56 | 36.14 | <0.001 | [1,2] [1,3] [2, 3] |

*The mean difference is significant if $p < 0.05$.

The results of the pairwise comparisons shown in Table 5 reveal significant between group differences in the intelligence phase ($F(2, 27)=39.69, p < 0.05$), design phase ($F(2, 27)=11.30, p < 0.05$), choice phase ($F(2, 27)=6.608, p < 0.05$), and utility scores ($F(2, 27)=36.14, p < 0.05$). This suggests that different decision support tools have varying effects on the different stages of the decision making process. Consistent with the expectation, pairwise comparisons

show that, EDS (M=5.31, SD=0.34) provides significantly better support for the intelligence phase than does PDS (M=4.12, SD=0.69). There are no significant differences in the level of support provided by EDS (M=4.90, SD=0.37) and PDS (M=4.56, SD=0.64) for the design and choice phases of the decision making process. Both EDS and PDS provide superior levels of support for all of the stages of the decision making process than LDS. Taken together the results indicate that EDS provides the best support for the decision making process followed by PDS and LDS respectively. In terms of the effect of differing levels of decision support on bid-quality, the pairwise comparisons also reveal that the EDS (M=73.49, SD=6.39) was able to generate significantly ($p<0.05$) superior quality bids for the bid-taker than PDS (M=58.35, SD=7.24) and LDS (M=46.56, SD=5.66). PDS results in superior ($p<0.05$) quality bids for the bid-taker than LDS. Taken together, these results provide support for H₁ which states that using EDS will result in better quality bids than using PDS or LDS and H₂ which states that using PDS will result in better quality bids than using LDS.

4.2. Experiment 2: Decision Support and Auction Structure

The second experiment was designed to test the relationship between two auction structure variables and bid-quality.

4.2.1. Method

The same training procedure and protocol employed in experiment 1 was used for the second experiment. The subjects in this study were undergraduate business students drawn from a large university in the Midwest. One hundred and six subjects participated in experiment 2. The multi-attribute software used in the first study was employed in the second study, but was modified to allow for the manipulation of the number of attributes and the number of bidders in the auction while maintaining the same bid scoring approach used in experiment 1.

To examine the effects of manipulating the number of attributes in an auction, the second experiment considered auctions with three different attribute levels – two, three and four. Bidders submitted bids on hard-drive [x_1] and price [x_3] for the two attribute auction, hard-drive [x_1] memory [x_2] and price [x_3] for the three attribute auction, and hard-drive [x_1], memory [x_2], price [x_3] and lead time [x_4] for the four attribute auction. Lead time refers to the amount of time it would take for the bidder to supply the item. Bids on x_4 could range from 1 day to 5 days in 1 day increments with 5 days being less desirable for the bid-taker. The bid-taker evaluated the bids in experiment 2 using the same function used in experiment 1 i.e. function 1. To assess the impact of manipulating the number of bidders, auctions with two, four and six bidders were considered. The number of subjects randomly allocated to each cell is summarized in Table 6.

Table 6: Treatments and Number of Subjects per Cell

| Treatment | | Number of subjects per cell |
|------------------------------------|--|-----------------------------|
| Number of attributes in the action | Number of competing bidders in the auction | |
| 2 | 2 | 22 |
| 3 | 2 | 22 |
| 4 | 2 | 18 |
| 2 | 4 | 20 |
| 3 | 6 | 24 |

4.2.2. Results

Multiple regression analysis was performed to analyze H₃ and H₄. Recall that H₃ proposes that increasing the number of attributes in a multi-attribute auction can have a negative effect on bid quality and H₄ suggests that increasing the number of bidders in a multi-attribute auction can have a negative effect on bid quality. Thus, the number of attributes and the number of bidders served as independent variables and the utility score which measures bid quality was the dependent variable. The regression equation is therefore:

$$\text{Utility Score (Bid Quality)} = \beta_0 + \beta_1 B_1 + \beta_2 A_2 + \varepsilon \quad [3]$$

Where

B₁= number of bidders

A₂ = number of attributes

Table 7 presents the results of the analysis. The average bid from each group rather than individual bids was used as the unit of analysis. The results indicate that the two structural variables explain 50.1 percent of the variance in the utility score. The ANOVA result suggests that overall relationship between structural variables and utility score is significant $F(2, 37) = 20.59, p<0.05$. Support was found for H₃; there is a significant negative relationship between number of attributes and bid quality $t(37) = -5.34, p<0.05$. H₄ is not supported. In fact, there is a significant positive relationship between the number of bidders and bid quality $t(37) = 2.79, p<0.05$.

Table 7: Relationship between structural variables and bid quality, Coefficients^a

| Model | Unstandardized Coefficients | | Standardized Coefficients | t | p-value |
|----------------------|-----------------------------|------------|---------------------------|--------|---------|
| | B | Std. Error | Beta | | |
| Constant | 86.176 | 4.003 | | 21.529 | <0.001 |
| Number of bidders | 1.899 | .680 | .319 | 2.791 | 0.008 |
| Number of attributes | -6.106 | 1.143 | -.610 | -5.342 | <0.001 |

a. Dependent Variable: Utility Score [Bid quality]

5. Discussion, Contribution and Future Research

This study sought to investigate 1) the relationship between decision support, the decision making process, and bid quality in multi-attribute reverse auctions and 2) the relationship between auction structure and bid-quality. The results from the analysis suggest that bid-takers in multi-attribute reverse auctions can positively influence the stages of a bidder's decision making process and bid quality by using decision support tools. Both EDS and PDS tools had a larger positive effect on the stages of the decision making process than the LDS tool. EDS tools provided the best support for stages of the decision making process. Such tools are characterized by having information about the bid-takers' weighting for various attributes, competitor bid information and suggestions of how a bidder can make improvements on a previously placed bid. The experiments demonstrated that small changes to the level of support e.g. not providing bidders with information about the bid-takers' preference can result in certain stages of the decision making process not being supported. Consequently, not supporting the entire decision making process can lower the quality of bids.

The fact that this study revealed that different decision support tools could influence different stages of the bid decision making process differently and subsequently bid quality is an important contribution to the literature and has important implications for the design of decision support for multi-attribute auctions. By conceptualizing the bidding process as a decision making process, this study demonstrates that Simon's [1960] decision process model serves as a potent framework for the systematic evaluation of the effectiveness of decision support tools developed for multi-attribute auctions. Rather than adopting an ad hoc approach to decision support as is typically the case, auction designers need to systematically evaluate the degree to which various decision support tools are able to facilitate the differing stages of the bidding process. For example, providing a tool that only offers the conventional computational support may be inadequate for realizing the best quality bids since computational tools will most likely impact the choice phase of the decision making process.

The second stage of this study investigated the relationship between structural variables in multi-attribute reverse auctions and bid quality for bidders with extensive decision support. Two structural variables were considered: the number of attributes and the number of bidders. The results of the analysis indicate that the benefits of extensive decision support diminish when the number of attributes increases. In other words, there is a limit to the number of attributes bidders can handle even if they are provided with extensive decision support tools.

The contribution of this finding for bid-takers is that, even though it may be tempting to incorporate a large number of attributes into a multi-attribute reverse auction, bid-takers need to exercise restraint and limit the number of attributes since it could potentially have a negative effect on bid quality. If bid-takers would like to receive bids on a large number of attributes they may wish to consider adopting different auction formats such as a multi-stage multi-attribute reverse auction. Such formats would allow auctioneers' to split their auction into stages where bidders first compete on the set of attributes most important to the bid-taker, then the top set of bidders from the first auction proceed to a second stage of bidding where they compete on a different set of attributes. A multi-stage approach could reduce the level of complexity and ultimately allow bid-takers to realize better quality bids than if all the attributes were incorporated into a single auction.

The final hypothesis in this study was not supported. In fact the experiments indicate that increasing the number of bidders had a positive effect on bid-quality. This finding is in line with studies which argue that adding more bidders in an auction increases the level of competition and ultimately results in better quality bids [Brannman, Klein, and Weiss, 1984; Bulow and Klemperer 1996]. One possible reason why the level of complexity may not increase to the extent that it jeopardizes auction performance as the number of bidders increases in multi-attribute reverse auctions could be as follows. If bids are ranked by the bid-taker and bidders can see the bids and the ranks, as was the case in this study, bidders may choose to only focus on the top ranked bidder and ignore other bidders when structuring their response bids. By adopting this approach they do not have to analyze the actions of other

competitors. Consequently, the level of complexity in the auction does not increase significantly; however, the top ranked bid stimulates competition resulting in higher utility scores for the bid-taker. The implication of this finding is that bid-takers may be able to explore the positive effect of bidder numbers without being concerned about the possibility that this structural variable may significantly increase the complexity of the auction and thereby diminish the benefits of decision support tools.

5.1. Contribution

To encapsulate, this study contributes to extant literature by highlighting that bidding can be viewed as a decision process and hence Simon's decision process model can be used as a potent framework to systematically assess the making effectiveness of decision support tools developed for multi-attribute auctions. Furthermore, it highlights that over and above the importance of providing support for each stage of bidders' decision making process, it is also vital for auctioneers to consider various structural variables when evaluating the effectiveness of decision support tools to use in multi-attribute reverse auctions. While it is important to realize that it is essential to build decision support tools that sufficiently facilitate every stage of the bid decision making process in multi-attribute reverse auctions, it is problematic to assume that a decision support tool remains equally effective under all structures. The findings of this study lay a foundation for a contingency perspective which emphasizes that the relative effectiveness of decision support tools in complex auctions are subject to change under differing structural conditions. Exploring the effects of structural variables hence allows us to gain a better understanding of the conditional boundaries under which a decision support tool works most or least effectively.

5.2. Future Research

Finally, it should be noted that like all studies, this study has limitations. For instance, the maximum number of bidders considered is six. The implication of adding more than six bidders to a multi-attribute reverse auction is unknown. The ramifications of having more than six bidders will have to be explored in future studies. Furthermore, future work may also wish to address other limitations of this study. For instance bid-quality may be compared when a multi-stage auction format is used versus when a single stage format is used, or the relationship between decision support tools and bidder experience can be explored. Future studies will also have to consider the impact of additional auction structural variables such as the number of units, the number of auction rounds, and different auction closing rules.

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