Information Revelation in Multi-Attribute Reverse Auctions: An Experimental Examination

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Abstract

This study experimentally examines the effects of information revelation in multi-attribute reverse auctions. In particular, two treatments are carried out: revelation of limit-sets which indicate the admissible bids, and revelation of limit-sets and winning bids. The results show no significant difference between the auctions with different information revelation in terms of allocative efficiency, joint gain, outcome equity and the bidders' profit. The buyer's profit in the auctions providing winning bids was, however, significantly higher than those auctions with limit-sets only. The latter auctions required more bids and rounds, but the bidders' concessions were much smaller. This indicates that the revelation of winning bids increases the bidders' competition and leads to quicker convergence with larger concessions. It was also found to reduce the differences in subjective outcomes between the winner and non-winner groups.

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1. Introduction

E-procurement is a key component in B2B commerce, through which businesses obtain goods and services [1, 2]. With advanced ICTs, e-procurement can improve the traditional procure-to-pay processes and increase the efficiency and effectiveness [3-5]. Given its advantages, e-procurement applications have been growing fast and continuously during the past decade. The market has reached $5 billion [6] and an annual growth rate of 8% to 12% is predicted by AMR Research and Forrester Research [6, 7].

Online auctions have gained popularity in procurement transactions for which price is the main concern. Standard (i.e., forward) auction mechanisms deal with the situation in which one seller organizes an auction and many buyers bid on the price. In procurement, reverse auctions have been implemented and used. In these auctions the roles of buyer and seller are reversed, i.e. the buyer organizes an auction and the sellers (suppliers) are bidders. Reverse auctions have been shown to achieve an average gross savings of 5-20 percent [8].

Most auctions are concerned with a single attribute, typically price. However, organizations are also often interested in values of attributes other than price. A survey by Ferrin and Plank [9] found that over 90% of purchasing managers based their decisions on both price and non-price variables (e.g., durability, service, lead-time, and trust). Typically these types of decisions have been made through negotiations; procurement managers negotiated with several suppliers in order to select one of them. Negotiation, however, is a difficult and costly process, in particular when one needs to negotiate with many counterparts.

Several approaches to multi-attribute auctions have been proposed [e.g. 10, 11]. Some aim at combining price with the total costs of all non-price attributes, others in aggregating all attributes into utility functions. Each of these mechanisms has limitations, including disclosure of buyer's preferences [10, 23], limited number of quantitative attributes [12, 13], and collusion [14, 15].

Information revelation has been an important aspect in mechanism design [19, 20]. Much effort has been put to experimentally examine the effects of different rules of information revelation in auctions, though only few studies have investigated the effects in multi-attribute auctions [21, 22].

The present study employs a multi-attribute auction system as a test bed which allows the implementation and manipulation of different rules of information revelation in the same software environment. The effects of these different rules can then be examined, controlling the characteristics of transaction tasks and participants (e.g. number of bidders, bidder's demographics). The key question is: *How does the level of information revelation affect the transaction process and outcomes?*

A laboratory experiment with two treatments was carried out: revelation of limit-sets only and revelation of limit-sets and winning bids. The outcomes are examined at both the individual and transaction level with economic measures and subjective responses.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature on information revelation. Section 3 presents the research model and hypotheses. Section 4 describes the experimental design and procedure, followed by Section 5 with the data analysis and results. Section 6 discusses the implications and limitations of this study.

2. Relevant literature

The different rules of information revelation are first summarized. Experimental studies on their effects are then reviewed.

2.1 Rules of information revelation

A common concern in multi-attribute auctions pertains to information that is revealed to the bidders. The minimum requirement for information revelation is that the information be sufficient for the bidders to make progressive bids, i.e., consecutive bids that are increasingly better for the buyer. The revealed information may be directly or indirectly related to the buyer's preferences in one or a combination of these four forms:

- Information about buyer's preferences [10, 23]: The preferences may be fully or partially revealed, and this information can be revealed before or during auction;
- Information constraining the admissible bids [21, 22]: The information about directions for allowable values of some or all attributes, constraints which provide limits on attribute combinations, bounds, and so on.
- Information about bids [24, 25]: The bidders may obtain detailed information about the winning bids, selected bids, or all bids;
- Information of bids' values [22, 26]: This may be the values of attributes only, the internal values (e.g., price, cost), or aggregated value of bids [26].

The present study considers the information revelation in a multi-attribute reverse auction mechanism in which the buyer is not required to explicitly disclose her preferences [27]. Instead, the information that is given to the bidders is similar to that in a single attribute auction. The information is comprised of the value range or value set for each attribute, which is called a "limit-set". It constrains or directs the bidder to provide only those attribute values which are acceptable for the buyer. A limit-set is based on the buyer's preferences and dynamically modified reservation levels.

Taking into account the reservation levels for all attributes, one or more of limit-sets are generated in every round (e.g., a three-attribute limit-set may be that price is not higher than $1000, lead time is no longer than 60 days, and warranty is not shorter than 36 months.). The number of limit-sets generated at any time depends on the auction design model.

Limit-sets indicate the admissible bids that the bidders can submit. From the bidder's perspective, knowledge of the current limit-sets is sufficient to make bids. An allowable bid is one that conforms to at least one of the limit-sets. This means that every bid has to follow the limits formulated in one of the limit-sets.

After the bidders submit their bids, the auction validates and compares the bids submitted and selects the best bid from the buyer's perspective (i.e. the winning bid yielding the highest value for the buyer). Then, the auction updates the limit-sets based on the winning bid and the auction design model.

The mechanism outlined above has been implemented in an e-procurement system. It allows, among others, to control the information revelation. Depending on the design rules, the bidders may be provided with the limit-sets only, the winning bids, and/or all bidders' bids (in every case they know their own bids).

2.2 Impact of information revelation

Experimental studies on different rules of information revelation have shown that they affect a bidder's bidding strategies, market competition, and both economic and subjective outcomes.

Bichler [10] conducted several experiments in which the bidders were given the buyer's value function. The results show that in this setting, multi-attribute auctions do not provide substantial benefits over comparable single-attribute auctions in terms of auction efficiency. In other words, even with fully-revealed utilities the additional complexity may outweigh the gains. While this may be the case, multi-attribute auctions allow for the exchange of goods that single attribute auctions do not.

Koppius and Van Heck [24] conducted experimental studies on the impact of information availability on the mechanism efficiency. The information availability specifies the type of information that is given and when, how and to whom it becomes available during the auction. They studied two types of multi-attribute English auctions: (1) auctions with unrestricted information availability, in which suppliers are provided with the winning bid, the corresponding bidder as well as the rating of the most current losing bids; and (2) auctions with restricted information availability, in which the bidders are informed only about the winning bid and corresponding bidder. Their experiments show that auctions with unrestricted information availability yield higher efficiency than auctions with restricted information availability.

Strecker and Seifert [25] analyzed the impact of preference revelation schemes on the efficiency of multi-attribute English and Vickrey auctions. They concluded that English auctions with revealed preference structure of the buyer are more efficient than Vickrey auctions and also, English auctions with hidden preferences. In a recent study [21], the bidders were provided with restricted information regarding the buyer's utility function: (1) indicative verbal information on the monotonicity constraints of the buyer's scoring rule prior to the auction (e.g. lower price, higher quality), and (2) the winning bid's attribute values. The results show that revealing the buyer's preferences increases allocative efficiency. Also, the bidders make more profits while the buyer's utility increases slightly.

Chen-Ritzo et al. [23] introduced a multi-attribute English auction where only partial information about the buyer's utility function was revealed. They showed that this variant performs better in terms of efficiency than a single attribute (price-only) auction. The outperforming of the multi-attribute over the single-attribute auction holds even though the bids in the multi-attribute auction were far away from solutions predicted by theory. Notably, complexity in the auction mechanism consumes some of the efficiency gains over price-only auctions. This observation however, contradicts the findings reported by Bichler [10].

In the framework proposed by Bellosta et al. [22], the information imparted by the buyer depends on the way she represents her preferences. When the representation includes a linear additive utility function, then the owner passes this utility and its lower bound. When the preferences are represented as a lexicographic aggregation model or a Tchebychev function, then the owner passes bounds imposed on the attribute values. This dependency is difficult to implement when the buyer does not make her preference model public, as is often the case [13, 28].

Teich et al. [29] suggest an information revelation rule in which the buyer prescribes a preference path; an ordered set of combinations of prices and non-priced attributes. The

preference path begins with an anchor point and the rule specifies that a point further from the anchor is preferred by the owner over the point that is closer to it. This allows the sellers to decrease the worth of their bids (as seen by the buyer) by proposing a combination that is more preferred by the buyer than that combination previously proposed. Burmeister [28] notes that one drawback of this method is the imposition of a restriction on bidders' choices, i.e., they are only allowed to bid on the preference path. Another limitation is the possibility for sellers to use the preference path to re-construct the buyer's value function.

Review of relevant literature indicates that every auction mechanism requires the disclosure of the buyer's preferences in order to provide sufficient information to bidders to make progressive bids. Disclosure of preferences, however, is problematic when the buying organization views these preferences as secret; disclosing them may endanger their competitive position.

The present study takes into account buyer's preference representation and information revelation, which allows for the separation of these two activities and the control of disclosure. The degree of disclosure is controlled by the buyer so that it is possible to move from giving the bidder the ability to re-construct the buyer's preferences to having preferences completely hidden so that their re-construction is not possible. It also allows both the buyer and bidders to use a compensatory method to compare or construct bids in which the information exchanged is within the constraints or reservation levels on the attribute values. The buyer is thus not required to explicitly disclose their preferences but the bidders obtain sufficient information to make progressive bids.

3. Research design

This study examines the effects of information revelation on auction process and outcomes. Figure 1 presents a conceptual model of this study.

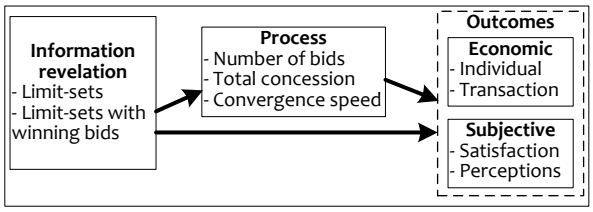

Figure 1. Research model

3.1 Variables and measurements

As shown in Figure 1, the independent variable considered in this study is the level of information revelation. Two levels of information revelation are manipulated in two treatments:

1. *Treatment 1*(T1): Limit-sets only, where only the limit-sets and the bidder's own bids are revealed during the auction process; and
2. *Treatment 2*(T2): Limit-sets with winning bids, where the current winning bids are revealed, as well as the limit-sets and the bidder's own bids.

In this study, both economic and subjective measures are used to measure the effects.

Economic indicators have been mainly used to measure individual and market performance in experimental and behavioral economics [30, 31]. Recent studies have also considered the participants' subjective responses [32, 33]. IS research on system usage suggests to take into account the objective performance in addition to subjective measures [17, 18].

In particular, the following economic measures are used to analyze the transaction process and outcomes [10, 24, 25, 34], including:

- Number of bids: this refers to the bids submitted during the auction process. At the individual level, it is the bids submitted by each bidder; at the transaction level, it is the total number of bids submitted in the same auction.
- Total concession: this refers to the value of bids that the bidders submit in the process. The total concession is the value difference or compromise that a bidder made through the auction process. It indicates the level of competition in auction.
- Convergence speed: this is the actual auction length, i.e. the amount of time to close the auction. It indicates how fast an auction will reach a result (i.e. contract).
- Economic outcomes: the economic outcomes of the contract resulted from an auction can be measured based on the buyer and suppliers' utility or value. This study considers the buyer's and suppliers' revenue and profit, their joint gain, allocative efficiency and outcome equity. The revenue is measured with a rating value on a scale of 0-100, and the profit is the difference between the revenue and the break-even point (i.e. cost and revenue are equal; there is no net loss or profit).

Auction mechanisms are implemented in e-procurement systems. Bidders, as participants of the auctions, are also the users of such systems. Users' perceptions of the auction process and outcomes may affect their evaluation of the mechanisms. Satisfaction has been a surrogate of effectiveness of information systems [35], and has been used in the assessment of various types of systems, including e-auctions [36, 37]. Existing literature indicates satisfaction involves outcomes [38, 39], self-performance [40, 41], and process [42, 43]. A multi-dimensional scale of participants' satisfaction in e-markets is adapted to procurement auctions in this study [44].

3.2 Hypotheses

Information about bids is not explicitly related to the buyer's preferences. However, bidders may be able to discover the buyer's value function by comparing their own bids and other available information (e.g. winning bids). In theory, the more information that is disclosed in an auction, the better the market performance will be in terms of efficiency (e.g. convergent speed and buyer's profit). Empirical results, however, were mixed with regard to revealing buyer's preferences [10, 23, 25]. Other studies found that higher levels of information revelation led to better market efficiency [24]. Studies on information transparency have also found that available market information on products and services from different suppliers increase market competition and thus cost savings [45-47]. With the higher level of competition, the suppliers need to make larger concessions to bid against each other. Thus, the effects of information revelation are hypothesized as follows:

H1: An increase in the level of information revelation will lead to …

A. smaller number of bids,

B. larger concession,

C. faster convergence speed, and

D. better economic outcomes.

Revealing more information may also increase the knowledge of the bidders about the buyer's preferences, which may lead to better joint outcomes and allocative efficiency [23, 24]. Moreover, more information revealed by the buyer may also increase the transparency of the process and thus the trust of the bidders [48]. Information about winning bids and other bidders' bids is valuable during the auction process; revealing such information may lead to better buyer-supplier relationships [49, 50]. User's evaluation of systems is affected by their performance and outcomes [51-53]. A higher level of information revelation reduces the participants' effort during the process, leads to better economic gains, and develops better relationships. Thus,

H2: An increase in the level of information revelation will lead to better subjective outcomes.

4. Experiment

A laboratory experiment was conducted to examine the effects of information revelation. The experimental design and procedure are described with the e-procurement task, subjects and instrument.

4.1 Experimental design

A business case is used, which involves contracting between a milk producer and several transportation service providers. The participants play the role of a sales representative for one of the providers. They are competing with each other through the auctions in order to win the contract. Each contract can be awarded to only one provider. The preferences are explained in the case (private information which is not known to the other parties). The reservation and aspiration levels of each company are also indicated.

The case has been designed in such a way that the theoretical winner for the contract is Universal Inc. (represented by Nart), who can bid as low as 10 (the company's break-even point) to provide the best offer to the buyer (yielding rating 92). However, because of the use of limit-sets in the mechanism design, in some situations this efficient alternative may be made inadmissible. If Worldwide Inc. (represented by Peeka) makes a pre-emptive offer at its reservation level (yielding rating 15) which has rating 90 for the byer, then the subsequent limit-set may remove some alternatives ranked between 90 and 92 even though they are better for the buyer. In that case Worldwide rather than Universal becomes a winner.

The distribution of the feasible solutions (or alternatives) between the buyer and each supplier can be identified based on their preferences. This is used as references when measuring the participants' performance (e.g. maximum achievable contract and profit).

The subjects for the suppliers are recruited from undergraduate students in the business school of a large Canadian university, while no buyer subjects are required. The subjects take an introductory course of management information systems. The experiment is part of their assignment for e-procurement worth 6%, considering both participation and performance.

4.2 Experimental procedure

The participants first sign up for the experiment online. Their demographical information is gathered via a registration form. The participants are then randomly matched up and assigned to consecutive sessions for the auctions. Each session lasts one hour and forty minutes,

including the time for preparation and questionnaires.

During the experiment, the participants first read the public information of the case (contextual information of the transaction) and the private information (preferences, constraints and objectives). This is followed by a pre-questionnaire before the auction, which contains three sets of questions: perceptions of the transaction task, aspiration and reservation levels. This examines the participants' expectations of the bidding space (the alternatives they may bid) and the contract.

The auction lasts 50 minutes at most, during which the participants submit bids on behalf of the companies they represent.

Once the auction closes, they are asked to fill out a post-questionnaire that collects subjective responses of the process and outcomes. The participants report their evaluation of the auction process in terms of performance, effort and experience. When they assess the outcomes and performance they may refer to their expectations.

The participants' activities during the transaction process are recorded in a database, which is used to analyze the transaction process and economic outcomes. The measures include:

- Transaction process: number of bids, number of rounds, total concession (both individual and transaction levels), time spent and convergence speed (at the transaction level);
- Economic outcomes: supplier's revenue and profit, buyer's revenue and profit, allocative efficiency, joint gain, and outcome equity.

5. Data analysis and results

5.1 Descriptive analysis

There were 179 students who participated in the experiment, among them four records were removed from the data as their auctions were terminated accidently. The subsequent analyses were then based on a sample with 175 participants. There were 26 auctions for T1 and 21 auctions for T2. On average, each auction involved 3.78 bidders and no significant differences were found between the two treatments in terms of number of bidders.

Most of the participants were between 20 and 25 years old as they were undergraduate students. About 45% were female and neither differs across the treatments and groups. The participants perceived their English proficiency and knowledge about auction above the average, and about 75% had never used an auctions system nor participated in such experiments previously. No significant difference in their understanding of the case and expectations of the transaction task was found using ANOVA.

5.2 Process and economic outcomes

The process efficiency can be measured by number of bids, number of rounds and time spent in the auction. They indicate the convergence of the auction with the time and effort the bidders spent in the auctions. Also, the opening bid and closing bid are also indicators of auction convergence in terms of the bidder's revenue. These variables were calculated at both the individual level and the auction (or transaction) level (Table 1).

Table 1. Comparison of auction process

	Winners			Non-winners			All
	T1	T2	Sig.	T1	T2	Sig.	Sig.
No. of bids	7.58	6.67	.26	6.03	5.27	.09	.05
No. of rounds	7.92	7.05	.23	6.85	5.84	.03	.02
Time spent	32.27	29.24	.42	27.74	22.68	.04	.03
Opening bid	75.62	77.71	.70	80.86	74.96	.06	.17
Closing bid	15.77	7.14	.08	31.15	17.95	.00	.00

At the individual level, the result shows that significant effort was made by the bidders in T1 than in T2. The bidders who were given only the limit-sets and their own-bids proceeded to later rounds and spent longer time for their auctions. On average, about one more round was required in those auctions. But interestingly, the same bidders did not make a large concession as those in the auctions with both limit-sets and winning bids. The winners played quite similarly in the two treatments, whereas the non-winners in T1 significantly took more rounds and time but made much less concession (average over 12 units) than the bidders in T2.

This result may indicate that the bidders did not find the limit-sets sufficient to make efficient bids. It may also indicate that the wining-bid information might provide more clues about the buyer's and other bidders' preferences and thus the bidders could bid more efficiently. Also, the fact that no differences on the opening bids but big differences on the closing bids indicate that the extra information—winning bids—given during the auction increased the competition levels and thus lead to quicker convergence with larger concessions.

At the transaction level, both the opening bid and the closing bid were significantly lower in T2 than in T1. However, there were no differences on the number of bids and rounds through which the auction converged. Auctions in both treatments were converged within eight rounds, given the initial maximum number of rounds up to ten.

The bidders obtained information about the break-even value and were told that they should not bid below this value because it would result in losses for their company. This was stated both in the case and again in the quiz administered to the participants. Nonetheless many winners bid below their break-even values, on average.

To provide comparable values for the winning bids from different bidders (roles) we calculated both the revenue and profit for the bidders and the buyer. In both treatments, the winner overbid and resulted in negative profit (Table 2). Relatively, the winning bids in T2 were lower than those in T1. The effect was that the buyers increased profit from 72.48 in T1 to 80.48 in T2. The may be due to the same reason that the information with winning bids led to "tough" bids and larger concessions.

Table 2. Comparison of economic outcomes

	T1	T2	Sig.
Bidder's revenue	15.77	7.14	.07
Bidder's profit	-2.12	-9.52	.16
Buyer's revenue	88.08	96.48	.04
Buyer's profit	72.48	80.48	.04
No. of dominating solutions	2.62	0.05	.13
No. of optimal solutions	1.15	0.05	.06
Allocative efficiency	59.82	68.04	.17
Joint gain			
- By revenue	103.85	103.62	.92
- By profit	69.96	70.95	.66
Outcome equity			
- By revenue	0.25	0.09	.11
- By profit	0.12	-0.10	.20

We also calculated the number of alternatives dominating the winning bid, that is, those alternatives which yield a higher profit for the winning bidder, the buyer or both, and for none of them the profit is lower. The winning bids made in T2 were, on average, Pareto optimal (the average no. of dominating alternatives is 0.05). The winning bids made in T1 were not Pareto optimal, because there were 2.62 dominating bids available, on average. Nevertheless, it also shows no significant difference of the allocative efficiency between the treatments, indicating that the auctions with different information revelation were equivalently efficient.

Considering the contract value for both the buyer and the service provider who won the contract, the joint gain and outcome equity by both their revenue and profit were compared between the two treatments. The results show little differences on joint gain and also on outcome equity in the auctions.

In addition, the winners' roles were checked to verify whether the theoretical winner would win the contract. Table 3 summarizes the number and percentage of winners and non-winners with their roles in the auctions.

Table 3. Winners/non-winners and their roles

	Winners			Non-winners			Total
	T1	T2	All	T1	T2	All	
Cres	6 23.1	7 33.3	13 27.7	20 27.8	14 25.0	34 26.6	47
Nart	7 26.9	9 42.9	16 34.0	19 26.4	12 21.4	31 24.2	47
Peeka	7 26.9	3 14.3	10 21.3	19 26.4	17 30.4	36 28.1	36
Rito	6 23.1	2 9.5	8 17.0	14 19.4	13 23.2	27 21.1	35
Total	26	21		72	56		175

The result shows that "Nart" as the theoretical winner indeed achieved the highest percentage of wins in both treatments, whereas the percentage was much higher than other roles in the auctions with winning bids revealed (42.9%). In the non-winner group, "Nart" was the lowest in T2 but not in T1. This indicates the revelation of winning bids enlarged the advantages of preferences. "Peeka" as another potential winner, however, performed only as well as "Nart" in T1 for both winners and non-winners. This implies that the theoretical winners indeed won when only the limit-sets were revealed. Also, "Peeka" had little chance to dominate other suppliers when the winning bids were revealed, which might be due to the higher competition and overbidding.

5.3 Subjective outcomes

Besides the economic measures, the participants' responses to the post-questionnaire were used to examine their evaluation of the auction process and outcomes. A factor analysis was first conducted to in order to obtain fewer measures that can be aggregated from the items and used to compare participant's perceptions in the two treatments. We used the maximum likelihood analysis with the oblimin rotation to extract identify the factors. The result extracted over 77.5% variance, and the factor loadings for all items were above 0.63. The factor loadings were then used as the weights to calculate a weighted sum for each factor from the participant's responses. In addition, one single-item was used to measure the perception of other bidders' competitiveness, and four items were used to measure the participant's overall experience or satisfaction.

In order to test the effects of the information revelation, we compared the overall groups, the

winner groups and the non-winner groups across the two treatments with the ANOVA techniques. The results indicate that there was little difference between the two treatments in terms of participants' satisfaction and perceptions (Table 4).

Table 4. Comparison of satisfaction and perceptions

	All bidders		Winners		Non-winners	
	T1	T2	T1	T2	T1	T2
Satisfaction						
Achievement	2.96	2.93	3.53	3.38	2.75	2.77
Performance	3.94	4.06	3.73	3.94	4.02	4.11
Overall	4.10	4.20	4.21	4.12	4.06	4.23
Perceptions						
Outcome	2.23	2.38	1.96	2.52	2.34	2.34
Competition	5.02	4.92	5.08	4.57	5.00	5.05
System	3.77	3.86	4.16	3.82	3.62	3.87

5.4 Group comparison

A comparison between winners and non-winners within each treatment was conducted to explore other possible factors that may affect the auction outcomes.

Although there were no differences between the participants in the two treatments in terms of their demographics, surprisingly the winners' experience with auction systems was significantly lower than the non-winners in T1. In T2, the winner's expected reservations were marginally higher than the non-winners.

Similar to the pattern as the comparison between treatments on the process, the number of bids and rounds and the closing bid were significantly differently between the winners and non-winners in both treatments (Table 5). While it took much more effort in T1 comparing to T2, the winners in both treatments were bidding in more rounds than the non-winners. Also, they made much lower closing bid in order to win the auctions.

Table 5. Winner and non-winner within each treatment

	T1			T2		
	Winner	Non-winner	Sig.	Winner	Non-winner	Sig.
Process						
No. of bids	7.58	6.03	.02	6.67	5.27	.02
No. of rounds	7.92	6.85	.09	7.05	5.84	.05
Time spent	32.27	27.74	.15	29.24	22.68	.04
Opening bid	75.62	80.86	.17	77.71	74.96	.57
Closing bid	15.77	31.15	.00	7.14	17.95	.01
Satisfaction						

	T1			T2		
	Winner	Non-winner	Sig.	Winner	Non-winner	Sig.
Achievement	3.53	2.75	.02	3.38	2.77	.09
Performance	3.73	4.02	.23	3.94	4.11	.48
Overall	4.21	4.06	.62	4.12	4.23	.71
Perceptions						
Outcome	1.96	2.33	.12	2.52	2.34	.44
Competition	5.08	5.00	.81	4.57	5.05	.23
System	4.16	3.62	.02	3.82	3.87	.82

In Treatment 1, the winners showed a significantly higher satisfaction with their achievement, while it's marginally significant in Treatment 2. The winners in T1 also provided more positive assessment on the system and information; however, it was not the same case in T2. This indicates that the differences of subjective outcomes between these groups were reduced when revealing the winning bids.

6. Discussion

This study considers the practical situations wherein B2B transactions involve multiple attributes of goods or services rather than price only and wherein the buyers prefer not to explicitly reveal their preferences. This requires that the bidders obtain sufficient information to make progressive and informed bids without knowledge of the buyer's preferences. The limit-sets comprised with value range of attributes indicate admissible bids during the auction process and are independent from the buyer's value function. They are thus considered as sufficient information to be revealed by the buyers.

Prior studies suggest disclosing the winning bids to improve the efficiency of auction outcomes and process. The present study experimentally examines the effects of revealing the limit-sets with and without winning bids in multi-attribute reverse auctions. The research model and hypotheses were tested. The results show that Hypothesis 1 was fully supported (A, B, C) except H1-D was partially supported. Hypothesis 2 was not supported, while a group comparison was conducted to further explore the effects between winners and non-winners.

The results show that the revelation of winning bids did not make significant improvements in terms of the allocative efficiency, joint outcomes and bidders' profit. This indicates that the revelation of limit-sets were indeed sufficient to guide the bidders for their bidding.

Moreover, revealing winning bids increased the buyer's profit while revealing only limit-sets decreased the process efficiency in terms of number of bids and rounds. Also, the bidders provided with the limit-sets and winning bids were more competitive in bidding, i.e. they made greater concessions. This is reasonable because the winning bids should be either on the boundaries of the space prescribed by the limit-sets (i.e. the buyer's reservation levels) or even further away from the boundaries. In the former case, they are same as the information indicated by the limit-sets, while in the latter case they indicate how far the current winners moved from the limit-sets towards the buyer's aspiration levels. This movement becomes faster when the bidders compete with each other in order to win the auction.

Several limitations of this study should be addressed for future research. In the experiment, a

test bed was used by university students to conduct a simulated auction task. Research in e-business has discussed both advantages and disadvantages of such setting. Future research may validate the hypotheses and findings with a field study where the systems are used by business professionals for real life transactions. Also, the transaction is relatively complex and the number of bidders in each auction is small. This may limit the findings to those transactions that involve business contracts with only a few potential and important suppliers. Future work may consider transactions with a larger number of suppliers for simpler transactions, which may require different rules of information revelation.

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