User Acceptance of Complex Electronic Market Mechanisms: Role of Information Feedback

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Abstract

This paper broadens the traditional scope of evaluating economic mechanisms that is traditionally done solely from an economic perspective. We evaluate the *usability* of *complex* economic mechanisms as well. In particular, we apply our approach to the evaluation of continuous combinatorial auctions, which represent a complex, sophisticated market mechanism that has not been generally available in the online marketplace but has the potential to enhance the economic efficiency of trade for assets with interdependent values. Intuitively, acceptance and usage of a complex mechanism can be fostered by providing information and tools that meet the users' task demands. Based on prior research and an analysis of the auction task, we develop practical and innovative information feedback schemes to reduce the cognitive burden of formulating bids in combinatorial auctions. Then, we use constructs from the technology acceptance model (TAM), which have been consistently shown to be key determinants of technology acceptance in the extant literature, to compare the usability of the mechanism under three different information regimes. In addition, we borrow constructs from marketing theory to assess the potential growth in adoption of the mechanism. We compare user perceptions of the three alternative designs in a laboratory experiment with over 130 subjects. Our study constitutes a complementary and novel approach in evaluating complex consumer-oriented electronic market mechanisms. Results indicate a higher adoption and usage potential of the mechanism with advanced information feedback, supporting the potential of combinatorial auctions as a user-acceptable market mechanism with appropriate feedback.

Keywords: *Technology acceptance, user perceptions, mechanism design, combinatorial auctions, information feedback.*

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1. Introduction

Rapid advances in the computing and information processing capabilities of modern information technology (IT) tools present opportunities to design and deploy innovative market mechanisms that can increase the net benefits to society. However, these advances often introduce complexities in the decision environment, not only in terms of the computational capabilities needed, but also in terms of the demands put upon users. For example, IT advances have been used in developing word processing software of increasing capabilities but also increasing complexities. As a result, users need to accept, incorporate, learn, and apply these new capabilities in order to leverage them.

This process has also been observed in the realm of e-commerce. Over the past decade, IT developments have allowed traditional single-item auctions to become immensely popular for the sale of goods and services over the Internet. Online auctioneers have implemented many different variations of classical single-item auctions, including auctions with multiple units. The similarity of these mechanisms to traditional off-line auctions has led to their ready acceptance with minimal strain on the users. As IT developments expand to afford more complex auction mechanisms (i.e., that allow bidders to express more complex preferences), both the capabilities and demands on users are affected.

Consider an auction for the sale of a number of equal-sized property lots surrounding a lake. A potential buyer may be more interested in acquiring two adjoining lots rather than two separate lots, since possessing adjacent lots can provide more options for development. Consequently, she may be willing to pay more for the two lots together than separately. However, the sale of the lots in separate single-item auctions limits her ability to express her superadditive valuation, and may lead to reduced revenue for the seller. Furthermore, the assets may not be won by persons who value them the most, resulting in loss of efficiency.[1] If the bidder bids too high on one of the adjoining lots in the hope of winning the other lot

[1] Efficiency (or allocative efficiency) of auctions is maximized when goods are acquired by persons who value them the most. Higher efficiency is a desirable goal in auctions because it leads to greater social welfare.

too, she exposes herself to a potential loss in the event that she is unable to win the second lot. C*ombinatorial auctions* are a multi-item trading mechanism that can mitigate this so-called *exposure problem* (Bykowsky et al. 2000) by allowing bidders to bid on the single lots as well as any combination of the lots (referred to as *packages* or *bundles*). For instance, if the lots are numbered A, B, C, etc., a bid of $2 million on the bundle {ABC} implies that the bidder is ready to pay $2 million only if she gets all three lots. When bidders' valuations of multiple items are interdependent, combinatorial auctions have been found to increase the efficiency, seller's revenue, and bidders' willingness to participate (Banks et al. 2003; Ledyard et al. 2002).

While combinatorial auctions have been used by a variety of industries for truckload transportation, bus routes, and industrial procurement (Cramton et al. 2006), they have not been available to the general consumer in the electronic marketplace. The initial barrier is a technical one: the absence of a suitable design that allows asynchronous combinatorial bidding similar to the ascending auctions of single items prevalent on the Web. The second barrier is one of user acceptance of the mechanism. People are not as familiar with combinatorial auctions, so their general acceptability is an open question. *Even if the technology is developed to overcome the technical barrier, will people adopt this complex auction mechanism?* In this paper, we address this question as well as the broader issues of designing user acceptable economic mechanisms and evaluating their market acceptance potential.

1.1 Research Questions and Approach

The most typical approach to evaluating economic mechanisms is to explore the economic properties of the systems (e.g., Bichler et al. 2009; Brunner et al. 2010; Chen-Ritzo et al. 2005; Kwasnica et al. 2005). More specifically, the interest lies in whether a new design (that provides different information or incentives from existing designs) produces higher efficiency – thereby increasing the social welfare. However, the technical merits of a mechanism provide no usage guarantees (Mathieson 1991). For complex economic mechanisms, such as the combinatorial auction, a complementary question is: *Will the users (i.e., the bidders) adopt the mechanism*? Such a question may be trivially true for simple systems, e.g., online single-item auctions; however, as complexity increases, the question becomes increasingly pertinent. This is certainly the case for complex online auctions, since a mechanism with an inferior design can be devastating to interesting business models. For example, Mercata.com tried to facilitate a volume-buying approach by lowering prices for all bidders as the number of bidders for a given item increased; however, since all the risk was borne by early bidders, no one had the incentive to bid first. This lack of temporal willingness to adopt the mechanism ultimately resulted in failure of the business model (Kauffman et al. 2002). In other words, favorable economic indicators do not automatically assure that users will adopt a mechanism as a mercantile process.

The focus of this paper lies in offering a complementary way of evaluating new and complex economic mechanisms beyond the economic criteria (e.g., efficiency, revenue etc.) that are traditionally used. Unlike institutional mechanisms, customer-facing mechanisms cannot succeed solely based on their economic properties. Our general approach follows the design science paradigm of Hevner et al. (2004). For the combinatorial auction mechanism, which is the context for this study, we create novel bidder support artifacts by designing information feedback schemes for bidders to facilitate bid construction. Since our approach designs several different information feedback artifacts, it meets the *design as an artifact* criterion of design science research. In addition, our context of novel online mechanisms clearly satisfies the *problem relevance* criterion of design science research. Within design science, we attempt to construct a practical approach to conducting continuous combinatorial auctions for more efficient delivery of goods to consumers that is acceptable to them.

Our research also satisfies the *iterative process* criterion of design science research since, once the technologies are designed, we test their user acceptance potential using laboratory experiments, where subjects participate in an auction and then respond to survey questions based on constructs proposed in two complementary approaches to initial adoption and its growth. The primary evaluative approach applies the technology acceptance model (TAM) (Bagozzi et al. 1992; Davis et al. 1989) to assess the usability of alternative designs. TAM derives from several theoretical models that have found user perceptions of an IT to be a key independent variable explaining acceptance and adoption of IT (Davis 1989; DeLone and McLean 1992; Rai et al. 2002; Seddon 1997; Venkatesh et al. 2003), such as the theory of reasoned action (TRA) (Fishbein and Ajzen 1975), the theory of planned behavior (TPB) (Ajzen 1991), social cognitive theory (SCT) (Bandura 1986), and innovation diffusion theory (IDT) (Rogers 1983). Differences among these models regarding the specific constructs and relationships posited exist; however, the common idea is that individual's beliefs and perceptions about IT have significant influence on usage intentions and actual usage behavior. Thus, to measure the impact of the task-oriented technology on the adoption potential of the mechanism, we rely on the TAM, which articulates the predictors of IT adoption. We examine whether technology that is designed for the task translates to a higher adoption potential of the novel mechanism. By so doing, we broaden the assessment of market mechanisms beyond purely economic measures, opening the door to better delivery of goods to consumers. Combinatorial auctions, as a mechanism that is novel, complex, and has high practical potential, constitute a perfect setting for applying the approach.

In tandem with TAM, we also draw from marketing theory (Keiningham et al. 2007; Morgan and Rego 2006) to address the adoption growth potential of the mechanism. This perspective provides a complementary, more future-oriented view of adoption, as a test of the convergent validity of the results. The measure we use is the Net Promoter Score (NPS) (Reicheld 2003), a metric used by many companies (such as GE, P&G, American Express, and Microsoft) to measure market growth potential by measuring customer loyalty (Reichheld 2006b). Reichheld (2006a) argues that the metric possesses greater predictive power of a company's growth prospects than the traditional customer satisfaction surveys. We describe the metric in more detail in Section 3.2.

The final criterion of design science research evaluation is *research contributions*. The approach and design described above allow us to make both practical and theoretical contributions. Our primary theoretical contribution is to analyze the task characteristics of a complex market mechanism toward the explicit goal of making the delivery mechanism more accessible to consumers. Using combinatorial auctions, we develop and test feedback schemes designed to promote a higher adoption potential of this novel mechanism. Our theoretical contribution is to go beyond the typical focus on economic performance and introduce the significance of adoption for evaluating the success potential of novel, complex electronic market mechanisms.

IS and OM research has significantly contributed to concepts, metrics, and methodologies of electronic market mechanisms in the past decade (e.g., Bapna et al. 2003; Bichler et al. 2009; Carter and Stevens 2007; Elmaghraby and Keskinocak 2003; Goes et al. 2010; Kwasnica and Katok 2007). However, the evaluation metrics have been primarily based on economic criteria. Despite the assumptions of traditional economic theory, individuals do not necessarily behave according to rational norms. Building a better mousetrap (from an economic standpoint) will not assure its use. Even though researchers (Hevner et al. 2004; Gregor and Jones 2007) have advocated the use of usability measures to evaluate the quality of design artifacts, the evaluation of economic mechanisms have been limited to their economic characteristics. We argue that it is important to expand the quality perspective to include the users' attitudes and beliefs. We believe that acceptability of an electronic market mechanism is a key dimension that has been largely ignored and is a core contribution of our research. This is a strong theoretical statement that pushes the traditional analysis of economic mechanisms beyond just economic performance. While researchers have argued this for organizational systems (Davis 1993), and the systems design literature has argued to take economics into account in the design of systems (Ba et al. 2001), the case has not been considered in the design of economic mechanisms. Especially vague has been the means for integrating economic thought into design. We demonstrate how this can be done using combinatorial auctions as a context.

From a practical standpoint, complex market mechanisms are already being introduced and hold promise as a continual growth area in electronic commerce for the deployment of goods to consumers in a way that is economically advantageous. As a result, our study offers practical contributions by investigating bidders' intentions to use a complex electronic market mechanism. If bidders show positive perceptions to the mechanism with the availability of task-oriented feedback, the pathway is opened to the development and wider use of these combinatorial auction mechanisms in the marketplace. Currently, applications of combinatorial auctions have been restricted to participation of knowledgeable bidders engaged in limited auction settings (e.g., Cantillon and Pesendorfer 2006; Caplice and Sheffi 2006). Our work is the first to explore the broader applicability of these potentially valuable mechanisms.

The paper is organized as follows. In Section 2, we provide details of the combinatorial auction mechanism, the task analysis of what bidders require to perform in such auctions, and the description of the task-oriented feedback designed to assist bidders. In Section 3, we discuss the theoretical background for our analysis of usability in the context of complex economic mechanisms, including TAM and adoption growth. In Section 4, we present the hypotheses concerning the impacts on user perceptions. In Section 5, we discuss our experimental environment including the survey administration. Section 6 presents the results, and Section 7 concludes with a discussion of our contributions and potential directions for future research.

2. Design Considerations for Continuous Combinatorial Auctions

Combinatorial auctions represent a class of multi-item trading mechanisms that allow bidders to consider dependencies among the items by permitting bids on combinations of items as well as on individual items. Prior research (Banks et al. 2003; Ledyard et al. 2002) suggests that this mechanism increases the net benefit (i.e., *allocative efficiency*) of trades when values of the traded assets exhibit synergies (e.g., they are complementary). Companies such as Procter & Gamble, Wal-Mart, Bridgestone, Ford, Compaq, and Staples have saved millions of dollars by employing combinatorial auctions in place of multiple single-item auctions for allocation of complementary assets (Cramton et al. 2006). These auctions form an excellent context for our study because, while the value of these auctions is well accepted, the mechanism has not been adopted in the consumer marketplace. Thus, there is a large potential for improved delivery of products to consumers that is unrealized. A major reason for this is that, until recently, the technology has not existed to carry out combinatorial auctions in a way that resembles traditional English auctions[2] with which consumers are familiar and that are common on the Web. Conducting such auctions has only become possible due to the huge advances in technology—more specifically, the massive improvements in the computing and information processing power that these auctions require—as well as the theoretical

[2] English auctions are the classic single-item ascending auctions.

bases for conducting combinatorial auctions in real time (Adomavicius and Gupta 2005). Thus, we are at the cusp of a potentially new, not yet available or adopted, technology-enabled mechanism, making this an excellent context for our study.

The task-analytic approach of designing technology is grounded in studies of expertise and, more specifically, draws on the Task-Technology Fit (TTF) theory within IS (Goodhue 1995; Goodhue and Thompson 1995). Studies of expertise have established that the notion of expertise is situation-dependent. Expertise depends upon the expert's specific knowledge and capabilities in the specific environment and its tasks (Ericsson 2006). This idea of the interconnection of personal capabilities and task is also central to the TTF theory, which suggests that technology is most likely to have a positive impact on performance when the capabilities of technology match the demands of the task that the users must perform. The cognitive fit literature asserts that problem solving works best when the available tools support the processes required to perform a task (Vessey 1991; Vessey and Galletta 1991). The positive impact on performance of the degree of fit between task and technology is also emphasized by the cognitive cost-benefit perspective (Payne 1982; Smith et al. 1982). Consequently, the theory provides the immediate basis for our approach in developing the computational machinery for conducting continuous combinatorial auctions that are acceptable to users for this complex, IT-enabled task. Exploiting the recent advances in technology and deriving from task analysis, we begin by identifying what is needed for a bidder to construct bids in a combinatorial auction. We then develop intuitive feedback to provide bidders in order to create a transparent environment designed to be similar to that of traditional English auctions and their counterparts prevalent on the Web. In our environment, bidders can potentially join an ongoing combinatorial auction at any time and are able to find up-to-date information in real time to assist their bidding.

In the next subsections we discuss the characteristics of combinatorial auctions that are different from traditional single-item auctions, and analyze the tasks that bidders are required to perform in such auctions. Following that, we provide details of the feedback schemes that we developed to assist those tasks.

2.1 Characteristics of Combinatorial Auctions

In single-item iterative auctions (e.g., English auctions), if a bidder is not the highest bidder, she must bid an amount higher than the current highest bid to have a chance of winning the auction. However, in combinatorial auctions, even if a bid is not currently winning,[3] it can still be among the future winners depending on the later bids. For example, in an auction of two items, A and B, if the current bids are: (1) \$5 for the single item {A}, (2) \$6 for the single item {B}, and (3) \$15 for the bundle {AB}, only the third bid is currently winning, assuming that the auctioneer's objective is to maximize his revenue. However, if a new bid of (4) \$11 for {B} arrives, then Bid 1, which was non-winning after the first three bids, will now be among the winning bids because the combination of Bids 1 and 4 (\$5 + \$11) is greater than the existing winning bid of \$15. Note, however, that after Bid 4 has been placed, Bid 2 can never win the auction because of the existence of a higher bid (of \$11) on the exact same item.

As this simple example illustrates, at any given stage of a combinatorial auction, a bid can be in one of three possible states: (1) currently winning (a *winning* state), e.g., the state of Bid 3 following the first three bids, (2) currently non-winning but with a possibility of winning in the future (a *live* state), e.g., the states of Bids 1 and 2 following the first three bids, and (3) currently non-winning with no chance of winning in the future (a *dead* state), e.g., the state of Bid 2 following the first four bids. This is in contrast to traditional single-item auctions, where a bid can only be in either of two possible states (winning/losing).

Because of this difference, successful bidding in combinatorial auctions is more complicated than it is for English auctions. Suppose we still have the three initial bids, (1) \$5 for {A}, (2) \$6 for {B}, and (3) \$15 for {AB}. At this stage, if a bidder chooses to place a minimum successful (i.e., non-losing) bid on {B}, she has a range of options available between \$6 + ε and \$10 + ε, where ε is the minimum bid increment. Any bid on {B} above \$10 (say, \$11) would make it winning at the current auction state along

[3] The winning bids in a combinatorial auction are those that combine together to generate the maximum revenue for the seller. Note that, unlike in single-item auctions, in combinatorial auctions there can be multiple bids winning at the same time.

with Bid 1, since \$5 + \$11 > \$15. Any bid on {B} above \$6 and up to \$10 would make the bid non-winning but with a chance of winning in the future, with a higher bid in the range [\$6, \$10] being more likely to become winning, because then a smaller increased bid for {A} is needed to make it winning. For example, a bid of \$9 on {B} becomes winning later if there comes a bid on {A} above \$6, but a bid of \$7 on {B} requires a bid on {A} above \$8 to become winning. Any of these might be viable bids for the bidder. Therefore, unlike in single-item auctions, in combinatorial auctions a potentially successful bid can take a range of values.

2.2 Bid Formulation

Typically, the task of a bidder in an open ascending auction is to understand the current state of the auction and place a bid that eventually enables her to maximize her surplus[4] (Krishna 2002; Milgrom 2004). In traditional single-item auctions, the minimum information that a bidder requires to reasonably perform these tasks are the current highest bid and a required bid increment. For instance, if the current winning bid is \$100 and the minimum bid increment is \$5, the bidder knows that the minimum provisionally winning bid would be \$105. Partly because of its minimal requirements on the user, the traditional auction is prevalent in e-commerce.

Now consider the equivalent information in a combinatorial auction. Generalizing in a straightforward manner, we can provide information regarding all the winning bids and a minimum bid increment. However, given the characteristics of combinatorial auctions as described in the previous section, even this information is incomplete for the bidders. For instance, if a bidder knows that the winning bids are \$100 on {ABC} and \$150 on {DEF}, and that the bid increment is \$5, she can easily compute the minimum winning bids on {ABC} (i.e., \$105), on {DEF} (i.e., \$155), as well as on {ABCDEF}(i.e., \$255), but not beyond these. This feedback case describes task information that parallels that in traditional, single-item auctions. But, while knowing the current winning bundles can help in the placement of a few selected bids, bidders are potentially interested in a large number of other

[4] A bidder's surplus reflects the increase in net worth of the bidder after the trade. For example, if a bidder values an asset at \$1000 but is able to acquire it for \$900 in an auction, her surplus is \$100.

combinations (e.g., {AB}, {AD}, or {CEF}) not covered by the winning bundles of bids and their combinations. Computing the winning bid on any other bundle can be a cognitively challenging problem. Furthermore, in bidding for these combinations, bidders might be interested in not only placing winning bids, but also placing bids that are not immediately winning but might become winning in the future (i.e., live bids). Therefore, other forms of feedback may be useful.

Promising possibilities in this regard are the *minimum price required to participate* (i.e., place a non-losing bid) and the *minimum price required to provisionally win* (i.e., place a currently winning bid) for any possible bundle. Unlike continuous single-item auctions, for combinatorial auctions these values differ. Therefore, providing the additional feedback should aid performance.

There are two caveats that need to be considered. First, researchers in many disciplines (e.g., Grise and Gallupe 1999; Jacoby 1984; Schick et al. 1990; Sparrow 1999) have found that the decision quality of an individual positively correlates with the amount of information he or she receives – up to a certain threshold. Beyond this threshold, more information impairs an individual's ability to properly interpret, synthesize, and integrate the information into their decision-making process (Chewning and Harrell 1990; O'Reilly 1980), and decision quality may deteriorate (Malhotra 1982). This suggests the value of simplifying the bidders' task by removing all dead bids from the auction interface, thereby reducing task complexity by shrinking the bid-space.

Still, we need to consider whether adding feedback beyond that usually available in traditional single-item auctions exceeds the bidders' cognitive capacities to process the information. If the added feedback does not assist the bidder to perform her task satisfactorily, she may not be willing to use the mechanism. As a partial answer, in terms of economic performance, a decrement in performance is not observed. Although the added feedback changes the balance of profits between the seller and buyers, economic performance in terms of efficiency does not deteriorate (Adomavicius et al., 2007). Still, this does not imply that acceptability increases with the added information nor that the winning bid information that is acceptable in the single-item auction is still acceptable in the combinatorial auction.

This leads to the second caveat: Even if economic performance does increase with feedback in combinatorial auctions, acceptability of the auction mechanism is not assured. This motivates the goals and design of the current study. The primary independent variable of the study is the nature of the feedback provided, as arising from this task analysis.

2.3 Feedback Schemes

One objective is to increase the acceptability of complex economic mechanisms through the application of task-oriented feedback. This objective is pursued in the complex decision environment of combinatorial auctions. As discussed earlier, we have identified the information needed by bidders in order to form bids based on the auction's current state, as is done in traditional single-item auctions. Supplying this information in a usable manner is expected to increase the acceptability of the technology, provided that the added information does not overly tax the bidder's capacity to use the information. For this purpose, we have developed two types of information feedback: *outcome feedback* and *price feedback*. We chose to provide the feedback in two levels (plus a baseline for comparison) in order to observe how perceptions change as a function of increasingly task-oriented feedback, as described below:

i. <u>*Level 1: Baseline feedback*</u> (control). In this case, all submitted bids are displayed to all bidders, but the outcome and price feedback are not provided. We use this level to measure the relative advantages of providing outcome and price feedback.

ii. <u>*Level 2: Outcome feedback*</u>. Besides being provided baseline feedback, the bidders are also continuously aware of which bids would win if the auction ended right then. From a technical perspective, this represents non-trivial feedback because winner determination in combinatorial auctions is a very computationally complex (i.e., NP-hard[5]) problem (Rothkopf et al. 1998; Sandholm 2000). This feedback level provides information comparable to the winning bid information in single-item auctions by providing feedback regarding the current outcome of the auction. This level of feedback is often provided in iterative combinatorial auctions before the

[5] In computational complexity, NP-hard (non-deterministic polynomial-time hard) problems denote a class of problems that do not have an efficient computational solution (i.e., a solution with running time that is polynomial with respect to the problem size). See Garey and Johnson (1979) for more details.

beginning of each new round by using a fast winner-determination algorithm. Our version provides the feedback of provisional winners in real time.

iii. *Level 3: Price feedback*. This level includes all information provided by the outcome feedback level. Furthermore, while outcome feedback assists bidders in one of their tasks – that of understanding the current state of the auction, price feedback also provides the type of information necessary to place an efficient bid by making the precise going prices for each bundle available. Price feedback includes two important deterministic bid evaluation metrics to aid bid formulation. For every possible bundle and throughout the auction, we supply: (1) the bid level below which bids can never be part of a winning bid combination; and (2) the bid level above which bids immediately become part of the set of currently winning bids. To ease complexity at this level, the losing (dead) bids also are removed from display. Thus, this level of feedback provides the assistance arising from the task analysis of combinatorial auctions that extends beyond the task demands of the single-item auction.

3. Theoretical Background

We derive our measures for evaluating the continuous combinatorial auction mechanism with different levels of feedback from the TAM and marketing literatures. We provide a brief background of the relevant variables from TAM in Section 3.1. We describe the marketing-based customer loyalty metric in Section 3.2.

3.1 Technology Adoption

IS research has long studied how and why individuals adopt new information technologies. We draw on this large body of research to select appropriate constructs as measures to assess the adoption potential of combinatorial auctions under different feedback conditions. The theory of reasoned action (TRA) (Ajzen and Fishbein 1980; Fishbein and Ajzen 1975), and its extension, the theory of planned behavior (TPB) (Ajzen 1991), have been widely employed in IS literature for the study of specific behaviors, such as electronic commerce adoption by consumers (Pavlou and Fygenson 2006). In general, these theories assert that actual behavior can be determined by the intention to perform that behavior. The two have been found to be highly correlated in numerous studies (e.g., Sheppard et al. 1988 present a review of the intention-behavior relationship).

The TAM (Davis 1989; Venkatesh et al. 2003) is an adaptation of the TRA to identify the determinants of initial acceptance and continued use of IS. Specifically, it examines the mediating role of two variables – perceived ease of use (PEOU) and perceived usefulness (PU) – in the relation between external variables and the potential of information system use. TAM posits that PEOU and PU are two variables or beliefs that determine attitude toward an IT, intention of use (IOU), and ultimately actual use. In the online context, Pavlou and Fygenson (2006) found these two variables to be important predictors of e-commerce adoption. Although TAM does not explicitly identify the external variables responsible for the PEOU or PU of a mechanism, prior research has looked at possible factors such as training interventions (Venkatesh and Davis 1996). Adams et al. (1992) similarly argued that these constructs may be used by system designers to obtain user feedback on different system features or design approaches, motivating the applicability of these constructs in the present context.

Davis et al. (1989) contend that favorable ease of use perceptions are necessary for initial adoption and continued use of IS. Venkatesh (1999) argues that, if a system is too difficult to use, it will likely be unable to overcome the hurdle of user acceptance. The importance of this construct has been emphasized in the human-computer interaction (HCI) literature (e.g., Gould and Lewis 1985) as well. TAM also suggests that PU depends upon PEOU, the idea being that the easier a technology is to use, the more useful it will be. All effects of external variables, such as design characteristics of systems, are posited to be completely mediated by these two key beliefs. Note that, while these constructs have been extensively tested for organizational decision making tasks, they have not been used in the context of economic mechanism design. Thus, prior to using the constructs, we will validate them (Section 6.1) within our context to assure that they operate as in past research when applied in the present context.

3.2 Adoption Growth

The growth perspective is complementary to technology acceptance. Since auctions are a communal mechanism, involving multiple participants and not just a single individual decision maker, we believe that successful adoption will be fostered with adoption growth by a market community. The constructs in the TAM are intended to predict mechanism usage, whereas the growth perspective adopts a more dynamic view in addressing the *potential growth* in intended usage. Thus, the growth perspective looks at a different aspect of intention of use. This dynamic view has not been theoretically connected to the other constructs in TAM, and so adoption growth is not explicitly included in that model. However, it is a relevant construct grounded in marketing theory (see for example, Keiningham et al. 2007; Morgan and Rego 2006) that is indicative of user acceptability, and so we include it in our study as a complementary measure allowing the assessment of convergent validity in our findings.

4. Research Hypotheses

In this section we delineate the hypotheses concerning the effects of feedback upon PEOU, PU, IOU, and adoption growth. As a whole, the hypotheses address the usefulness of the task analysis for designing this feedback, the use of appropriately designed technology for facilitating adoption in a complex environment, and the value of considering user adoption variables in evaluating market mechanisms. The study is designed to test whether appropriate technology aimed at lowering the cognitive burden on the participants can promote the user acceptance of the complex market mechanism of combinatorial auctions.

Thus, the hypotheses originate with the task-based design of feedback. Specific tasks require specific types of technological functionalities to complete. When technology enables a person to accomplish her task by providing task-appropriate data, the gap between task and technology narrows. In online auctions, a bidder’s task is to place efficient bids by processing several pieces of information, such as the existing highest bid and the minimum ask price. Combinatorial auctions represent an environment for which computing winning bids and subsequently calculating the minimum bid prices constitute cognitively complex exercises. Outcome feedback, which includes identification of the currently winning bids, is a non-trivial feedback that assists bidders in understanding the state of the auction. Therefore, outcome feedback is expected to be of greater assistance in meeting the demands of the task than just baseline feedback. Price feedback not only identifies the currently winning bids, but also provides information regarding the minimum price levels to place a non-losing or a winning bid on any bundle. Therefore, price feedback is expected to further ease the cognitive burden beyond what is possible with outcome feedback.

Of key interest is the effect of this feedback upon user acceptance. The extent to which a user finds participation in the auction mechanism effortless and the extent to which the mechanism appears useful depend on the alignment between the task and feedback. This logic leads us to arrive at the specific hypotheses as detailed in this section; we now state each of the effects as distinct hypotheses.

PEOU is the extent to which a person believes that using a system does not require much effort to perform her task. A better fit between the task requirements and the technology to execute the task can be expected to substantially lessen the processing effort of the bidders resulting in higher ease of use. Since each increasing level of feedback is geared towards increasingly meeting the demands of the task, we propose:

***Hypothesis 1a*:** Perceived ease of use will be higher in the case of outcome feedback than in the case of baseline feedback.

***Hypothesis 1b*:** Perceived ease of use will be higher in the case of price feedback than in the case of baseline feedback.

***Hypothesis 1c*:** Perceived ease of use will be higher in the case of price feedback than in the case of outcome feedback.

PU is the extent to which a person believes that using a system will aid in improving her task performance. If a system provides a good fit with the task, bidders should find the system to be useful. Because the outcome and price feedback would provide the bidders with information (currently winning bid, bid amount needed to win, etc.) that is analogous to the information readily available in other more familiar online auctions, we believe the availability of such feedback in combinatorial auctions will make these auctions more usable for the bidders. Therefore, these feedback schemes meet the task requirements of the bidders better. Since higher levels of feedback will allow the bidders to comprehend the environment better and participate in the auctions more effectively, bidders can be expected to perceive the mechanism as more useful. Furthermore, TAM suggests a positive influence of PEOU on the PU of the mechanism.

***Hypothesis 2a*:** Perceived usefulness will be higher in the case of outcome feedback than in the case of baseline feedback.

***Hypothesis 2b*:** Perceived usefulness will be higher in the case of price feedback than in the case of baseline feedback.

***Hypothesis 2c*:** Perceived usefulness will be higher in the case of price feedback than in the case of outcome feedback.

From a design perspective and as part of analyzing the task components, in addition to understanding the aggregate impact of each level of feedback, we are also interested in understanding the usefulness of each component of the feedback provided. Price feedback consisted of three distinct components (two price levels and removal of losing bids) in addition to the components of outcome feedback. The price feedback as a whole is expected to heighten perceived usefulness; however, we are also interested in the perceived usefulness of each aspect of the feedback (i.e., each of the two price levels and the removal of losing bids) to better understand the sources of any obtained usefulness gains. To do so, in the outcome and price feedback conditions, questionnaire items evaluating the usefulness of each feedback element were included. To assess the impact of these feedback elements, we tested whether the bidders were positively inclined toward each element.[6]

According to TAM, the IOU of a system is determined by the combination of PEOU and PU. Since we are hypothesizing an increased PEOU and also an increased PU with higher levels of feedback, based on this TAM hypothesis, we propose:

[6] Note that, in the outcome feedback case, only one additional feedback measure was provided (identification of winning bids) compared to the baseline case. Therefore, the test of Hypothesis 2a precludes any further analysis.

Hypothesis 3a**:** The intention of use will be higher in the case of outcome feedback than in the case of baseline feedback.

Hypothesis 3b**:** The intention of use will be higher in the case of price feedback than in the case of baseline feedback.

Hypothesis 3c**:** The intention of use will be higher in the case of price feedback than in the case of outcome feedback.

As a measure of adoption growth, we use the Net Promoter Score (NPS) (Reicheld 2003). For calculating the NPS of a product, users are asked the question: "How likely are you to recommend Product X to a friend or colleague?" The responses typically are scored on a zero-to-ten scale, where ten denotes "extremely likely" and zero "not at all likely." The responders are sorted into three clusters: (i) promoters, those giving ratings of nine or ten; (ii) passives, giving seven or eight; and (iii) detractors, between zero and six. NPS is the percentage of promoters minus the percentage of detractors. The higher the score, the more customers are happy with the product or service experience and are willing to recommend it to a friend. A 12-point difference in NPS has been reported to lead to doubling of a company's growth rate on average (Reicheld 2006b). We pose a similar question and calculate this metric for each of our three feedback schemes in order to gauge their relative growth potential.

Since feedback is expected to reduce the cognitive load on participants and help them perform better, we believe that a mechanism with better feedback will increase favorable word of mouth. As the quality of feedback is increased, it is expected that there will be more promoters of the mechanism and fewer detractors. Since NPS is the difference between the percentage of promoters and detractors, we arrive at the following hypothesis:

Hypothesis 4a**:** The Net Promoter Score will be higher in the case of outcome feedback than in the case of baseline feedback.

Hypothesis 4b**:** The Net Promoter Score will be higher in the case of price feedback than in the case of baseline feedback.

Hypothesis 4c**:** The Net Promoter Score will be higher in the case of price feedback than in the case of outcome feedback.

5. Research Methodology

We conducted a laboratory experiment drawing from theoretical and empirical advances in experimental economics (e.g., Holt 2007) related to the design of auctions. In the experiment, bidders participated in simulated auctions and recorded their perceptions regarding the mechanism following auction completion.

5.1 Experimental Environment

We constructed a combinatorial auction environment where bidders compete to acquire hypothetical real-estate properties around a lake. The bidders can bid on individual lots as well as any combination of the lots. The valuation structure of the assets was created so that bidders benefit by acquiring adjoining lots (as it can afford more options for development) as a single bundle rather than separately. The individual-lot valuation structure used in this study is shown in Figure 1a.

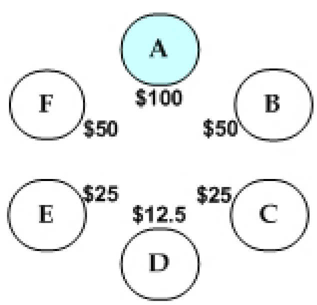

Figure 1a. Values of individual lots.

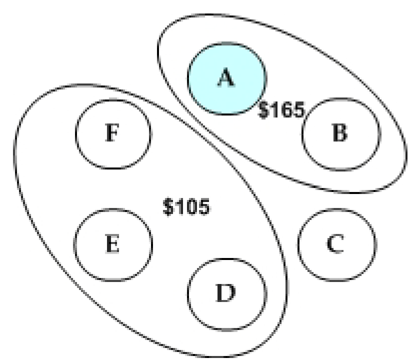

Figure 1b. Values of combinations of lots.

A lot, designated the *preferred lot*, is identified for each bidder participating in the auction. This lot (Lot A in Figure 1a) has the highest value for the bidder, with remaining values decreasing by 50% as the lots are further from the preferred position. We introduce s*uperadditivity* by adding 10% to the additive valuation of the lots for each adjoining lot in the bundle, thereby creating complementarities. Thus, if the valuations of the individual lots are as depicted in Figure 1a, then the valuation of the bundle {AB}, with one adjoining lot, is ($100 + $50) * 1.1 = $165.00, and that of bundle {DEF}, with two adjoining lots, is ($50 + $25 + $12.50) * 1.2 = $105.00, as shown in Figure 1b. The value of bundles without any adjoining lots is additive. For instance, if the values of the individual lots are as shown in Figure 1a, the value of bundle {ACE} is $150.00, i.e., the sum of the values for lots A, C, and E.

This setup, similar to the experimental environment of Banks et al. (2003), allows both for compactly describing the scenario to the participants as well as for building a simulation of the auction environment. We conducted several simulation runs with computerized bidding agents as well as pilot tests with human bidders to refine the parameters of our model before carrying out our main experiments. All the auctions reported in this paper were conducted with six items and three bidders. The preferred lots for the three bidders were A, C, and E respectively. With this design, the valuation structure is identical for each subject, allowing us to analyze their responses together.

The three levels of feedback mentioned in Section 2.3 formed our three experimental treatments, manipulated between-subjects. The three treatments differed only in the amount of feedback provided to the bidders. In the first treatment, which is the control, the bidders could see all the bids that have been placed, as they are being placed. No other feedback was provided. In our second treatment, outcome feedback was added, i.e., in addition to displaying all the bids, the winning bids at any given state of the auction were identified. Every time a bid was placed, the set of winning bids was recalculated. In our third treatment, we added price feedback to help bidders formulate their bids in addition to identifying the bids and winning bids at every stage. As mentioned earlier, this consisted of a specification of, for any bundle that they chose and given all the other bids at that state of the auction: (1) the minimum amount they needed to bid for their bid to stand a chance of winning in the future, and (2) the minimum they needed to bid for their bid to be winning right now. All bids that stood no chance of winning at any subsequent state of the auction were also removed from the display. The minimum bid increment was set at $1, i.e., only integer bids were allowed. Screen snapshots of the three interfaces are shown in Appendix A1.

5.2 Subjects

We conducted a total of 51 auctions over 15 experimental sessions. Three to four auctions were simultaneously conducted in each session. We excluded seven auctions from our analysis, because in these at least one bidder mistakenly placed a bid significantly higher than the valuation. In each case the bidder immediately notified us of the mistake; however, since our design disallowed bid withdrawal, we had to exclude those auctions. The remaining auctions were as follows: 14 auctions with baseline feedback (Treatment 1), 15 with outcome feedback (Treatment 2), and 15 with price feedback (Treatment 3). Subjects were randomly assigned to a specific treatment, and were not allowed to participate in more than one auction. The 132 unique participants in these 44 auctions were all undergraduate business students, who responded to volunteer solicitation announcements throughout the business school campus. The average age of the subject pool was 20 years; 55% were male.

5.3 Procedure

As in any online auction where bidders are usually unaware of the number of other bidders interested in the commodity, the participants in our experiments were not told how many other participants were competing in the same auction. Instructions explaining the rules of the auction were read aloud at the beginning of each session. The instructions were followed by short tests to ensure that the participants understood the rules of the auction and were familiar with the bidding process. The auctions as well as the surveys were entirely computerized. The bidders could bid continuously and place as many bids as they wanted on as many bundles as they wanted between the start and end of the auctions. The minimum duration of each auction was 15 minutes; after the first 13 minutes, the auction stopped whenever no bids were placed for 2 minutes.[7] Each auction lasted approximately 27 minutes on average.

The bidders were not given a fixed budget; the final compensation scheme was a fixed amount of $10 plus an amount based on the property lots the individual won in proportion to their retained surplus. Surplus was calculated as the difference between the bidders' valuation of the item(s) and their winning bid(s). Consequently, bidders' profits were positive, zero, or negative depending on whether their winning bid was less than, equal to, or greater than their valuation, respectively. If they did not win any lot, their profit was zero. Average payout was $17 per subject. Participants were paid privately at the end

[7] This *soft closing* rule was adopted to eliminate any *sniping* behavior, wherein bidders wait until the last second to bid.

of the study in sealed envelopes.

5.4 Survey Administration

In each session, prior to reading the instructions for the auction, a background survey was administered to record several control variables, including age, gender, and prior experience with online auctions. Questions were also asked regarding the subjects' proficiency with computers.

A second survey, intended to record the user perceptions, was administered following the completion of the auction. Validated items from prior research, tailored to our context, were used as manifest variables (see Appendix B) for the latent constructs in the TAM.

The items for PEOU and PU were adapted from past studies.[8] For the IOU construct we slightly modified the item that has been used in previous research. In general the IOU question for past research was based on the fact that the technology that the respondents use is part of their day-to-day work activity and hence direct questions regarding their intentions to use could be asked. However, for a new economic mechanism, similar questions are difficult to ask since the respondents may never have the opportunity to use such a mechanism. The mechanism that we are studying is not implemented anywhere yet, nor are the student participants in our study required to use it anywhere. Thus, instead of asking whether they intend to use it, we asked whether they would encourage anyone to participate in such auctions. This question has been shown in marketing literature to capture consumer loyalty and growth potential (Keiningham et al. 2007; Morgan and Rego 2006). To maintain a consistent user interface for survey items, responses to this question were also measured on a 7-point Likert scale, anchored by "strongly disagree" and "strongly agree" just as for all the items in Appendix B.

Finally, we added items probing perceptions of the individual components (i.e., two different price levels and removal of dead bids) that were added to the price feedback condition compared to the outcome feedback condition. Those in the price feedback auctions who saw the components were asked

[8] For PU, two of the items refer to the auction mechanism and two refer to combinatorial auctions in general. Since the subjects had no past experience with combinatorial auctions, these were expected to be equivalent; their perceptions of combinatorial auctions were based entirely on their experience with our mechanism. The validity checks (in Appendix 3) substantiated this expectation.

for the usefulness of each of them. Those in the outcome feedback auctions, who did not receive these components, were asked for the potential usefulness of each of them, had the subjects received them.

6. Results and Discussion

As noted earlier, subjects were randomly assigned to one of three treatments. Of the bidders who participated in Treatment 1 (baseline), 69% reported that they had prior experience of participating in online auctions; 63% for Treatment 2 and 56% for Treatment 3 reported similar experiences. We analyzed the data to see if the user perceptions had any significant correlations with prior familiarity of the subjects with online auctions. No such dependence was found, so all are combined in the subsequent analyses.

6.1 TAM Validation

Before testing our hypotheses presented in Section 4, we verified the validity of the TAM in the present context using the partial least squares (PLS) method. We validate that the measures, adapted from prior studies, behave in the same way in the present context. PLS performs a confirmatory factor analysis, where the pattern of loadings of the measurement items on the latent constructs is specified explicitly in the model. Then, the fit of this pre-specified model is examined to determine its convergent and discriminant validities. The descriptive statistics of the constructs along with their composite reliability are shown in Table 1. Data (N=132) for all the measures were standardized. The internal consistencies of all the variables are considered acceptable since the reliability measures exceed 0.80 (Barclay et al. 1995).

Table 1. Summary statistics of the survey constructs for pooled data.

Construct	Mean (SD)	Composite Reliability
1. Perceived Ease of Use (PEOU)	5.655 (1.016)	0.904
2. Perceived Usefulness (PU)	5.021 (1.251)	0.917
3. Intention of Use (IOU)	4.984 (1.482)	1.000

As shown in Table 2, the loadings of all our measurement items are considerably higher than their corresponding cross-loadings, with significant *t*-values at the .001 alpha level on the respective latent constructs. This demonstrates convergent validity of all the constructs.

Table 2. Loadings and cross-loadings of the measurement variables.

	PEOU	**PU**	**IOU**
PEOU1	**0.825*****	0.565	0.493
PEOU2	**0.817*****	0.386	0.369
PEOU3	**0.829*****	0.569	0.521
PEOU4	**0.878*****	0.569	0.564
PU1	0.647	**0.898*****	0.640
PU2	0.606	**0.903*****	0.656
PU3	0.328	**0.738*****	0.500
PU4	0.538	**0.883*****	0.619
IOU1	0.592	0.708	**1.000*****

*** $p < 0.001$.

We analyze the average variance extracted (AVE) of our measures in order to demonstrate the discriminant validity of our model. AVE measures the amount of variance that a construct secures from its indicators relative to the amount due to measurement error (Chin 1998). AVEs were generated using the bootstrap resampling technique. As shown in Table 3, the square root of AVE for each latent construct is greater than the correlations among any pair of latent constructs. Further, the square root of the AVEs for each construct is greater than the minimum recommended level of 0.50 (Fornell and Larcker 1981). Thus the discriminant validity of our model is confirmed.

Table 3. Correlation matrix and average variance extracted (AVE) for constructs.

	PEOU	**PU**	**IOU**
PEOU	**0.837**		
PU	0.636	**0.858**	
IOU	0.592	0.708	**1.000**

The diagonal elements (in bold) represent the square root of the AVE.

In addition to the validity tests of the individual constructs, we also tested their validity through the expected interrelationships among the constructs. The PLS path coefficients and the explained variance (R^2) for the endogenous constructs are shown in Figure 2. In PLS analysis, observing the R^2 values of endogenous variables and the coefficients of structural paths quantifies the explanatory power of the structural model. All the relationships posited in TAM hold. In line with previous studies (Davis 1989; Venkatesh 1999), the PU-IOU relationship is found to be stronger ($\beta = .56$) than the PEOU-IOU relationship (β = .24). Most of the impact of PEOU on IOU is mediated by PU. Overall, the model explains 54% ($R^2 = 0.54$) of the variance in IOU.

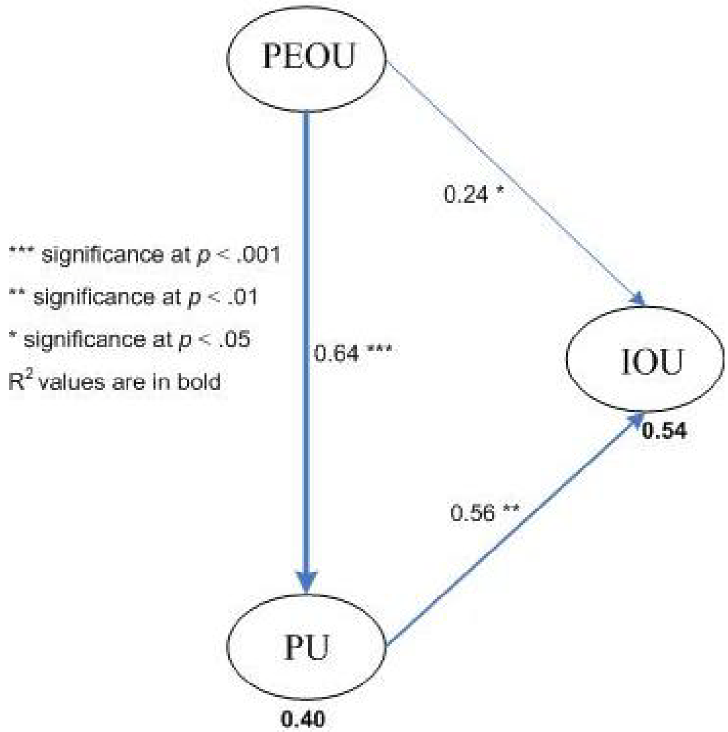

Figure 2: PLS results for TAM validation

6.2 Descriptive Statistics

All the scales exhibit good psychometric properties for each feedback type. Reliability estimates of all the latent constructs were above 0.80, with most being over 0.90, suggesting high degree of reliability. The data are shown in Table 4. Convergent and discriminant validity were supported by results from factor analysis with cross-loadings lower than 0.20.

Descriptive statistics of the constructs for each of the three treatments are shown in Table 5. As expected, the mean of every construct can be seen to be monotonically increasing with levels of feedback. We check whether the mechanism is perceived positively using *t*-tests for the means of each of the constructs against a hypothesized mean of 4.0, which is "neutral" in our response scale. The results are shown in Table 6.

Table 4. Reliability measures of the latent constructs.[9]

Construct	Number of Items	Baseline Feedback	Outcome Feedback	Price Feedback
1. Perceived Ease of Use (PEOU)	4	0.828	0.894	0.953
2. Perceived Usefulness (PU)	4	0.894	0.944	0.925

Table 5. Summary statistics of the survey constructs.

	Baseline Feedback	Outcome Feedback	Price Feedback
Number of respondents	42	45	45
Construct	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*
1. Perceived Ease of Use (PEOU)	5.214 (0.922)	5.822 (0.845)	5.900 (1.136)
2. Perceived Usefulness (PU)	4.601 (1.137)	5.100 (1.221)	5.333 (1.299)
3. Intention of Use (IOU)	4.452 (1.400)	5.044 (1.397)	5.422 (1.514)

Table 6. Mean comparison test results for hypothesized mean = 4.0.

Construct	Baseline Feedback	Outcome Feedback	Price Feedback
1. Perceived Ease of Use (PEOU)	t = 8.539 $p < 0.000$*** ($PCT_{>4} = 86\%$)	t = 14.458 $p < 0.000$*** ($PCT_{>4} = 93\%$)	t = 11.218 $p < 0.000$*** ($PCT_{>4} = 93\%$)
2. Perceived Usefulness (PU)	t = 3.427 $p < 0.000$*** ($PCT_{>4} = 69\%$)	t = 6.040 $p < 0.000$*** ($PCT_{>4} = 89\%$)	t = 6.885 $p < 0.000$*** ($PCT_{>4} = 87\%$)
3. Intention of Use (IOU)	t = 2.094 $p = 0.021$* ($PCT_{>4} = 50\%$)	t = 5.014 $p < 0.000$*** ($PCT_{>4} = 67\%$)	t = 6.298 $p < 0.000$*** ($PCT_{>4} = 76\%$)

Note: All tests are one-tailed. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.
$PCT_{>4}$ – percentage of respondents above 4.0

We find strong evidence that the users agreed that the mechanism in general was easy to use and useful in all conditions. This is an encouraging result for the development of technology for complex environments based on task analyses. It is also encouraging for online marketplaces, since the cognitive complexity of the environment has so far hindered the acceptance of this mechanism for general use, even when numerous research has shown that, when assets exhibit dependencies, combinatorial auctions

[9] IOU was measured using only one item and so has not been shown in the table.

increase overall social welfare. Our results constitute a step toward showing that, with appropriate feedback schemes, it is feasible to deploy combinatorial auctions even for consumer-centric (such as business-to-consumer and consumer-to-consumer) electronic commerce, where the participants cannot be expected to be as sophisticated as the economists participating in the FCC spectrum auctions,[10] for example.

6.3 Hypotheses Tests

To test the impact of feedback (i.e., the treatment variable) on the dependent variables, we first conduct multivariate analysis of variance (MANOVA). The multivariate test of differences between groups is statistically significant (Wilk's λ = 0.8915; $F(6, 254) = 2.50$; $p < 0.05$). Follow-up multivariate comparisons between groups (feedback types) show (Table 7) that the impact of outcome feedback on the dependent variables is significantly different from that of baseline feedback (Wilk's λ = 0.938; $F(3, 127) = 19.5$; $p < 0.04$) as is that of price feedback (Wilk's λ = 0.907; $F(3, 127) = 4.36$; $p < 0.01$); however, the impact of price feedback is not statistically different from that of outcome feedback at the 95% level.

Table 7. Results of MANOVA postestimation.

Feedback	Wilk's lambda	F
Outcome vs. Baseline	0.938	$F(3, 127) = 2.81$*
Price vs. Baseline	0.907	$F(3, 127) = 4.36$**
Price vs. Outcome	0.987	$F(3, 127) = 0.57$

** $p < 0.01$ * $p < 0.05$.

Table 8. Hypotheses test results – Tukey's HSD test.

Construct	Outcome > Baseline	Price > Baseline
1. Perceived Ease of Use (PEOU)	*	*
2. Perceived Usefulness (PU)		*
3. Intention of Use (IOU)		*

Note: * indicates that the feedback levels are significantly different from each other on this dimension using a Tukey test with family level $\alpha = .05$. A blank indicates no significant difference.

In order to test the changes in the constructs between any two levels of feedback for the pairwise

[10] Since 1994, the FCC has been using some form of combinatorial auction for the sale of electromagnetic spectrum.

contrasts of interest, we conducted Tukey's Honestly Significant Differences (HSD) test to verify our propositions comparing user perceptions with varying levels of feedback. Table 8 presents the results using a family level α of .05 to check for significant differences among the dependent variables.

Price feedback as well as outcome feedback made the mechanism significantly easier to use compared to the baseline case (H1a and H1b supported). With the availability of feedback that catered to their processing needs, the amount of effort that the bidders needed to expend in placing a bid progressively diminished. However, as is evident in Table 7, price feedback did not result in any significant increase in user perceptions compared to outcome feedback (H1c, H2c, and H3c not supported).

The increase in PEOU with outcome and price feedback resulted in the increase of PU and IOU with price feedback compared to the baseline case (H2b and H3b supported) but not with outcome feedback compared to the baseline case (H2a and H3a not supported).

Thus, we do not see significant differences between the outcome and price feedback cases or between outcome and baseline feedback (except for PEOU) for the TAM variables. In order to focus on each of the three additional components of feedback that we provided in the price feedback case beyond those provided in the outcome feedback case, we analyzed the survey questions that were targeted at the usefulness of each of the three components of price feedback separately, namely: (i) the minimum amount required to place a winning bid on a chosen bundle, (ii) the minimum amount required to place a bid that has a chance to win in the future (i.e., a live bid) on a chosen bundle, and (iii) the removal of bids that had no chance of winning in the future. The results for the price feedback case, where all these three pieces of information were available to the users, are displayed in Table 9. The means for all the three dimensions are significantly higher than 4.0, indicating an agreement among the users that these decision aids were useful.

We gave similar items to the participants receiving just outcome feedback, asking whether they thought that these decision aids would have been useful to them if they were provided. The results, shown in Table 10, also point to the potential usefulness of the additional decision aids with all means indicative of an agreement.

Table 9. Incremental usefulness of Price Feedback.

Question	Mean (SD)	Responses > 4.0	Mean Comparison with Hypothesized mean = 4.0
1. I found the information provided by the system, regarding the minimum I needed to bid in order for my bid to be winning, useful in formulating my bids.	6.089 (1.221)	91%	t = 11.472 p < 0.001***
2. I found the information provided by the system regarding the minimum I needed to bid in order for my bid to stand a chance of winning in the future, useful in formulating my bids.	6.022 (1.234)	93%	t = 10.995 p < 0.001***
3. I found the removal from the bid history, of the bids that stood no chance of winning in the future, useful in formulating my bids.	5.889 (1.654)	80%	t = 7.658 p < 0.001***

Note: All tests are one-tailed assuming equal variances. *** p < 0.001.

Table 10. Potential Usefulness of Price Feedback.

Question	Mean (SD)	Responses > 4.0	Mean Comparison with Hypothesized mean = 4.0
1. In this auction, if the system provided information regarding the minimum I needed to bid in order for my bid to be winning, it would have been useful in formulating my bids.	5.667 (1.796)	78%	t = 6.224 p < 0.001***
2. In this auction, if the system provided information regarding the minimum I needed to bid in order for my bid to stand a chance of winning in the future, it would have been useful in formulating my bids.	5.889 (1.369)	78%	t = 9.257 p < 0.001***
3. In this auction, if the bids that stood no chance of winning in the future were removed from the bid history, it would have been useful in formulating my bids.	5.711 (1.854)	80%	t = 6.191 p < 0.001***

Note: All tests are one-tailed assuming equal variances. *** p < 0.001.

How is it that the individual components of the price feedback can be perceived as useful and yet the feedback overall is not perceived as more useful than the outcome feedback auctions where these components are omitted? One possibility is that the result is due to the limitations of using a between-subjects design in a context for which bidders do not have prior experience. Combinatorial auctions are not commonplace and were new to the subjects. It could be that they recognized the value of feedback in each case (i.e., outcome and price feedback) and responded positively in each case (as supported by Table 5). However, the responses were not sensitive to the differences between the conditions because there was no common context to which the two groups could compare and respond. Thus, the bidders in the outcome feedback condition responded positively to the PU of their feedback and did not temper their response, having no knowledge from experience of what additional feedback might have been possible. A second possibility, as hinted in Section 2.2, is that the usefulness of the individual components did not sum to an overall perception of usefulness due to the aids being countered by the increased complexity that the added feedback provides to the mechanism. The feedback has good fit to the task, but it is added information; information overload is a possibility. At this point, we can clearly conclude that feedback is beneficial with respect to the TAM constructs; however, the best level of feedback is still open.

As another perspective on this issue, we apply the marketing view incorporated in the Net Promoter Score (NPS). In our context, NPS provides a stand-alone metric of relative likelihood of increased growth in acceptance and constitutes an independent measure of the impact provided by different levels of feedback. For the purpose of calculating the NPS, we coded the responses to the question: "I will encourage my friends to participate in this type of auction" as follows: promoters (6 and 7), neutral (5), and detractors (1, 2, 3, and 4). The NPS is calculated by subtracting the percentage of detractors from the percentage of promoters. The results are shown in Table 11.

Table 11. Net Promoter Score (NPS) for different levels of feedback.

	Baseline Feedback	Outcome Feedback	Price Feedback
Promoters[a]	24%	40%	56%
Detractors[b]	50%	33%	24%
NPS	- 26 points	7 points	32 points

[a] All pairwise proportions between different levels differ, one-tailed z, p < .10.
[b] Baseline feedback proportion differs from other feedback level proportions, one-tailed z, p < .10. Outcome and price feedback proportions differ, one-tailed z, p < .20.

We find that with baseline feedback the mechanism has net detractors. This emphasizes the need to provide appropriate task-oriented feedback to conduct continuous combinatorial auctions. With the provision of outcome feedback, we have net promoters of the mechanism, the number of which increases even more with the provision of price feedback.

Overall, we find the NPS increasing by at least 25 points with each increasing level of feedback (H4a, H4b and H4c supported). It is reported that, on average, a 12-point increase in NPS corresponds to a doubling of a company's growth rate (Reichheld 2006b, p.43). Thus, our results indicate a potential for almost quadrupling of growth in adoption rate of the mechanism with each more advanced level of feedback. This market-oriented measure thus shows a performance-based advantage favoring the added price feedback. The additional assistance could potentially generate a more favorable word-of-mouth for the mechanism compared to outcome feedback, positively influencing the growth in adoption of the mechanism.

7. Discussion and Conclusions

Advancements in information technology have expanded the capabilities of economic mechanisms and have opened the way for increasingly complex consumer-oriented mechanisms. Even when the technical issues of providing these new capabilities can be addressed, the issue of user acceptance of complex mechanisms remains. Combinatorial auctions represent such a mechanism that has had limited use and has not yet made inroads into general consumer e-commerce settings due to its complexity. Several researchers have suggested that the cognitive complexity of assessing the auction state and formulating an effective bid in combinatorial auctions is a major hurdle preventing this economically attractive mechanism from reaching its full potential (Kwasnica et al. 2005; Porter et al. 2003).

Our research advances the development of the requisite artifacts for making this complex trading environment more intuitive and transparent to participants. To achieve this goal and following the paradigm of design science (e.g., Hevner et al. 2004), we use a task-analytic approach to designing feedback schemes that provide a good task-technology fit. This approach has general applicability as well as provides a pathway to expanding the opportunities for use of combinatorial auctions in e-commerce.

The feedback schemes are task-oriented, i.e., they are designed to assist bidders in the bid-making process. Hence, we expected the feedback to improve the perceptions of users regarding the fit and usefulness of the technological capabilities with the task at hand, leading to increased intentions of using the mechanism. To test our hypotheses, we conducted a laboratory experiment, providing three different levels of feedback to bidders, and measured whether making the mechanism more transparent causes significant differences in user perceptions of the environment. Our results point towards significantly higher levels of adoption potential with the feedback schemes that we have designed. Furthermore, the mechanism exhibits higher growth potential with increasingly higher levels of feedback.

Our major contributions in this paper lie in: (1) offering an alternative means of evaluating complex economic mechanisms, one that is grounded in IS and marketing theories, and (2) demonstrating the use of task analysis to develop acceptable technology for complex, beneficial economic mechanisms. Traditionally, the quality of economic mechanisms has been solely evaluated based on their economic properties, such as efficiency and seller's revenue, neglecting the usability aspect of the systems. In this paper we argue that, while focusing primarily on the technical characteristics of the systems may have been sufficient for simple mechanisms such as online English auctions, as complex mechanisms are developed, we can no longer ignore usability as an essential evaluation criterion of the mechanisms. Since implementing advanced mechanisms such as combinatorial auctions would not have been possible without sophisticated technological artifacts, we follow the recommendations of design theorists (Hevner et al. 2004) to propose and demonstrate the application of usability measures to the evaluation of complex electronic market mechanisms.

Numerous studies have emphasized the relevance of favorable user perceptions for the acceptance and continued usage of IS. Specifically, the widely used TAM has laid out the two most significant predictors of behavioral intentions to use an IS: perceived ease of use and perceived usefulness. While this model has been widely used in the context of organizational decision-support systems, we use it in a novel way – for evaluating decision aids for an economic mechanism. Given that conducting continuous combinatorial auctions has been made technologically feasible by the vast improvements in computing and information processing capabilities, we use the TAM to demonstrate the effectiveness of our feedback schemes in fostering potentially higher adoption. Furthermore, using the NPS metric from the marketing literature, we show that the auctions with higher levels of feedback generate net promoters of the mechanism, whereas the baseline case has net detractors. The results of our study reveal that our approach lowers the hurdle of participating in combinatorial auctions considerably, thus enhancing their potential long-term usage in electronic markets.

Our approach demonstrates positive potential for developing technology using the design science paradigm, which leads to good user acceptance in a complex environment. The study sheds light on whether complex economic mechanisms can be made more acceptable to users by using technological innovation, as well as introducing acceptability as an important and useable criterion for evaluation to complement traditional economic analyses.

REFERENCES

Adams, D. A., Nelson, R. R., Todd. P. A., 1992. Perceived usefulness, ease of use, and usage of information technology: A replication. MIS Quarterly 16 (2), 227-247.

Adomavicius, G., Curley, S. P., Gupta, A., Sanyal P., 2007. Design and Effects of Information Feedback in Continuous Combinatorial Auctions. In Proceedings of the International Conference on Information Systems (ICIS).

Adomavicius, G., Gupta, A. 2005. Towards Comprehensive Real-Time Bidder Support in Iterative Combinatorial Auctions. Information Systems Research 16 (2), 169-185.

Ajzen, I., 1991. The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes 50, 179-211.

Ajzen, I., Fishbein, M., 1980. Understanding Attitudes and Predicting Social Behavior, Prentice-Hall, Englewood Cliffs, NJ.

Arora, A., Greenwald, A., Kannan, K., Krishnan, R., 2007. Effects of Information-Revelation Policies Under Market-Structure Uncertainty. Management Science 53 (8), 1234-1248.

Ba, S., Stallaert, J., Whinston, A. B., 2001. Research Commentary: Introducing a Third Dimension in Information Systems Design—The Case for Incentive Alignment. Information Systems Research 12 (3), 225-239.

Bagozzi, R. P., Davis, F. D., Warshaw, P. R., 1992. Development and Test of a Theory of Technological Learning and Usage. Human relations 45 (7), 659-686.

Bandura, A., 1982. Social Foundations of Thought and Action: A Social Cognitive Theory, Prentice-Hall, Englewood Cliffs, NJ.

Banks, J., Olson, M., Porter, D., Rassenti, S., Smith, V., 2003. Theory, Experiment and the Federal Communications Commission Spectrum Auctions. Journal of Economic Behavior and Organization 51 (3), 303-350.

Bapna, R., Goes, P., Gupta, A., 2003. Replicating Online Yankee Auctions to Analyze Auctioneers' and Bidders' Strategies. Information Systems Research 14 (3), 244-268.

Barclay, D.W., Higgins C., Thompson R., 1995. The Partial Least Squares (PLS) Approach to Causal Modeling: Personal Computer Adaptation and Use as an Illustration. Technology Studies 2(2), 285-309.

Bichler, M., Shabalin, P., Pikovsky, A., 2009. A Computational Analysis of Linear Price Iterative Combinatorial Auction Formats. Information Systems Research 20 (1), 33-59.

Brunner, C., Goeree, J. K., Holt, C. A., Ledyard, J. O., 2010. An Experimental Test of Flexible Combinatorial Spectrum Auction Formats. American Economic Journal of Microeconomics 2 (1), 39-57.

Bykowsky, M. M., Cull, R. J., Ledyard, J. O., 2000. Mutually Destructive Bidding: The FCC auction problem. Journal of Regulatory Economics 17 (3), 205-228.

Cantillon, E., Pesendorfer, M., 2006. Auctioning Bus Routes: The London Experience, in: Cramton, P., Shoham, Y., Steinberg, R. (Eds.), Combinatorial Auctions, The MIT Press, Cambridge, MA, pp. 573-592.

Caplice, C., Sheffi, Y., 2006. Combinatorial Auctions for Truckload Transportation, in: Cramton, P., Shoham, Y., Steinberg, R. (Eds.), Combinatorial Auctions, The MIT Press, Cambridge, MA, pp. 539-572.

Carter, C. R., Stevens, C. K., 2007. Electronic Reverse Auction Configuration and its Impact on Buyer Price: A Laboratory Experiment. Journal of Operation Management 25 (5), 1035-1054.

Chen-Ritzo, C. H., Harrison, T. P., Kwasnica, A. M., Thomas, D. J., 2005. Better, Faster, Cheaper: An Experimental Analysis of a Multi-Attribute Reverse Auction Mechanism with Restricted Information Feedback. Management Science 51 (12), 1753-1762.

Chewning Jr, E., Harrell, A. M., 1990. The Effect of Information Load on Decision Makers' Cue Utilization Levels and Decision Quality in a Financial Distress Decision Task. Accounting, Organizations and Society 15 (6), 527-542.

Chin, W. W., 1998. The Partial Least Squares Approach to Structural Equation Modeling, in: Marcoulides, G. A. (Ed.), Modern Methods for Business Research, Lawrence Erlbaum Associates, Mahwah, NJ, pp. 295-336.

Cramton, P., Y. Shoham, R. Steinberg., 2006. Introduction to Combinatorial Auctions, in: Cramton, P., Shoham, Y., Steinberg, R. (Eds.), Combinatorial Auctions, The MIT Press, Cambridge, MA, pp. 1-14.

Davis, F. D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13 (3), 319-340.

Davis, F. D., 1993. User Acceptance of Information Technology: System Characteristics, User Perceptions and Behavioral Impacts. International Journal of Man-Machine Studies 38 (3), 475-487.

Davis, F. D, Bagozzi, R. P., Warshaw. P. R., 1989. User acceptance of computer technology: A comparison of two theoretical models. Management Science 35 (8), 982-1003.

DeLone, W. H., McLean, E. R., 1992. Information systems success: The quest for the dependent variable. Information Systems Research 3 (1), 60-95.

Elmaghraby, W., Keskinocak, P., 2003. Combinatorial Auctions in Procurement, in: Billington, C., Harrison, T., Lee, H., Neale, J. (Eds.), The Practice of Supply Chain Management, Kluwer Academic Publishers, pp. 245-258.

Ericsson, A. K., 2006. An Introduction to the Cambridge Handbook on Expertise and Expert Performance: Its Development, Organization, and Content, in: Ericsson, A. K., Charness, N., Feltovich, P. J., Hoffman, R. R. (Eds.), Cambridge Handbook on Expertise and Expert Performance, Cambridge University Press, Cambridge, UK, pp. 3-20.

Fishbein, M., Ajzen, I., 1975. Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. Addison-Wesley, Reading, MA.

Fornell, C., Larcker, D. F., 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research 18 (1), 39-50.

Garey, M. R., Johnson, D.S., 1979. Computers and Intractability: A Guide to the Theory of NP-Completeness. W.H. Freeman, New York.

Goes, P., Karuga, G., Tripathy, A., 2010. Understanding Willingness-to-Pay Formation of Repeat Bidders in Sequential Online Auctions. Information Systems Research 21 (4), 1-18.

Goodhue, D. L., 1995. Understanding User Evaluations of Information Systems. Management Science 41 (12), 1827-1844.

Goodhue, D. L., Thompson, R. L., 1995. Task-Technology Fit and Individual Performance. MIS Quarterly 19 (2), 213-236.

Gould, J. D., Lewis, C., 1985. Designing for usability: Key principles and what designers think. Communications of the ACM 28 (3), 300-311.

Gregor, S., Jones, D., 2007. The Anatomy of Design Theory. Journal of the Association for Information Systems 8 (5), 312-335.

Grisé, M. L., Gallupe, R. B., 1999. Information Overload: Addressing the Productivity Paradox in Face-to-Face Electronic Meetings. Journal of Management Information Systems 16 (3), 157-185.

Hevner, A. R., March, S. T., Park, J., Ram, S., 2004. Design Science in Information Systems Research. MIS Quarterly 28 (1), 75-105.

Holt, C. A., 2007. Markets, Games, & Strategic Behavior, Pearson Addison Wesley.

Jacoby, J., 1984. Perspectives on Information Overload. The Journal of Consumer Research 10 (4), 432-435.

Kauffman, R. J., Wang, B., Miller, T., 2002. Strategic 'Morphing' and the Survivability of E-Commerce Firms. In Proceedings of the 35th Hawaii International Conference on System Sciences (HICSS).

Keiningham, T. L., Cooil, B., Andreassen, T. W., Aksoy, L., 2007. A Longitudinal Examination of Net Promoter and Firm Revenue Growth. Journal of Marketing 71 (3), 39-51.

Krishna, V., 2002. Auction Theory, Academic Press.

Kwasnica, A. M., Ledyard, J. O., Porter, D., DeMartini, C., 2005. A New and Improved Design for Multiobject Iterative auctions. Management Science 51 (3), 419-434.

Kwasnica, A. M., Katok, E., 2007. The Effect of Timing on Bid Increments in Ascending Auctions. Production and Operations Management 16 (4), 483-494.

Ledyard, J. O., Olson, M., Porter, D., Swanson, A., Torma, D. P., 2002. The First Use of a Combined Value Auction for Transportation Services. Interfaces 32 (5), 4-12.

Malhotra, N. K., 1982. Information Load and Consumer Decision Making. "The Journal of Consumer Research 8 (4), 419-430.

Mathieson, K., 1991. Predicting User Intentions: Comparing the Technology Acceptance Model with the Theory of Planned Behavior. Information Systems Research 2 (3), 173-191.

Milgrom, P. R., 2004. Putting Auction Theory to Work, Cambridge University Press.

Morgan, N. A., Rego, L. L., 2006. The Value of Different Customer Satisfaction and Loyalty Metrics in Predicting Business Performance. Marketing Science 25 (5), 426.

O'Reilly III, C. A., 1980. Individuals and Information Overload in Organizations: Is More Necessarily Better? The Academy of Management Journal 23 (4), 684-696.

Pavlou, P., Fygenson, M., 2006. Understanding and predicting electronic commerce adoption: An application of the theory of planned behavior. MIS Quarterly 30 (1), 115-144.

Payne, J. W., 1982. "Contingent Decision Behavior," Psychological Bulletin, (92:2) 1982, 382-402.

Porter, D., Rassenti, S., Roopnarine, A., Smith, V., 2003. Combinatorial Auction Design. Proceedings of the National Academy of Sciences of the United States of America 100 (19), 11153-11157.

Rai, A., Lang, S. S., Welker, R. B., 2002. Assessing the validity of IS success models: An empirical test and theoretical analysis. Information Systems Research 13 (1), 50-69.

Reichheld, F. F., 2003. The one number you need to grow. Harvard Business Review 81 (12), 46-54.

Reichheld, F. F., 2006a. The microeconomics of customer relationships. MIT Sloan Management Review, 73-78.

Reichheld, F. F., 2006b. The Ultimate Question: Driving Good Profits and True Growth. Harvard Business School Press.

Rogers, E. M., 1983. Diffusion of innovations, The Free Press, New York.

Rothkopf, M. H., Pekec, A., Harstad, R. M., 1998. Computationally Manageable Combinatorial Auctions. Management Science 44 (8), 1131-1147.

Sandholm, T., 2000. Approaches to Winner Determination in Combinatorial auctions. Decision Support Systems 28 (1-2), 165-176.

Schick, A. G., Gordon, L. A., Haka, S., 1990. Information Overload: A Temporal Approach. Accounting Organizations and Society 15 (3), 199-220.

Seddon, P. B., 1997. A respecification and extension of the DeLone and McLean model of IS success. Information Systems Research 8 (3), 240-253.

Sheppard, B. H., Hartwick, J., Warshaw, P. R., 1988. The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research. The Journal of Consumer Research 15 (3), 325-343.

Smith, J., Mitchell, T., Beach, L., 1982. A Cost-Benefit Mechanism for Selecting Problem-Solving Strategies: Some Extensions and Empirical Tests. Organizational Behavior and Human Performance 29 (3), 370-396.

Sparrow, P., 1999. Strategy and Cognition: Understanding the Role of Management Knowledge Structures, Organizational Memory and Information Overload. Creativity and Innovation Management 8 (2), 140-148.

Venkatesh, V., Davis, F. D., 1996. A Model of the Antecedents of Perceived Ease of use: Development and Test. Decision Sciences 27 (3), 451-481.

Venkatesh, V., 1999. Creation of favorable user perceptions: Exploring the role of intrinsic motivation. MIS Quarterly 23 (2), 239-260.

Venkatesh, V., Morris, M. G., Davis, G. B., Davis, F. D., 2003. User acceptance of information technology: Toward a unified view. MIS Quarterly 27 (3), 425-478.

Vessey, I., 1991. Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature. Decision Sciences 22 (2), 219-240.

Vessey, I., Galletta, D., 1991. Cognitive Fit: An Empirical Study of Information Acquisition. Information Systems Research 2 (1), 63-84.

Appendix A1 – Screen snapshots of the three treatments.

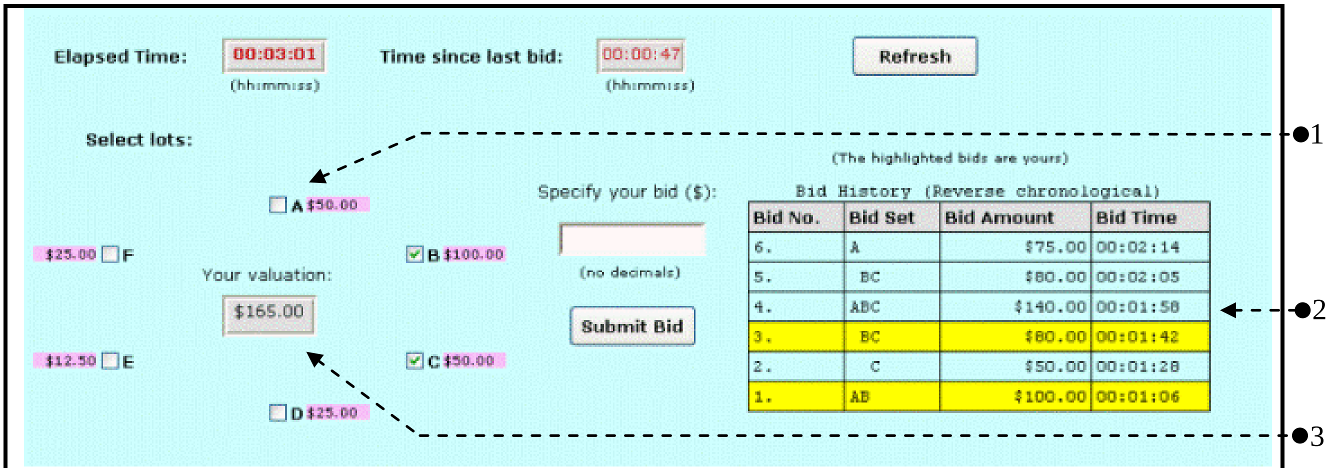

Figure A1a. Auction interface for baseline feedback.

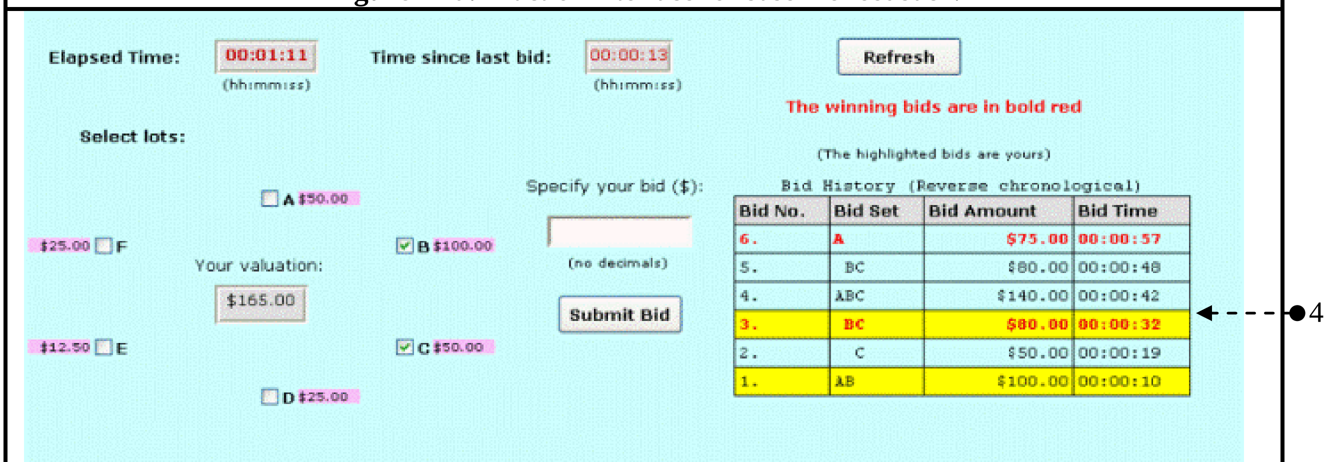

Figure A1b. Auction interface for outcome feedback.

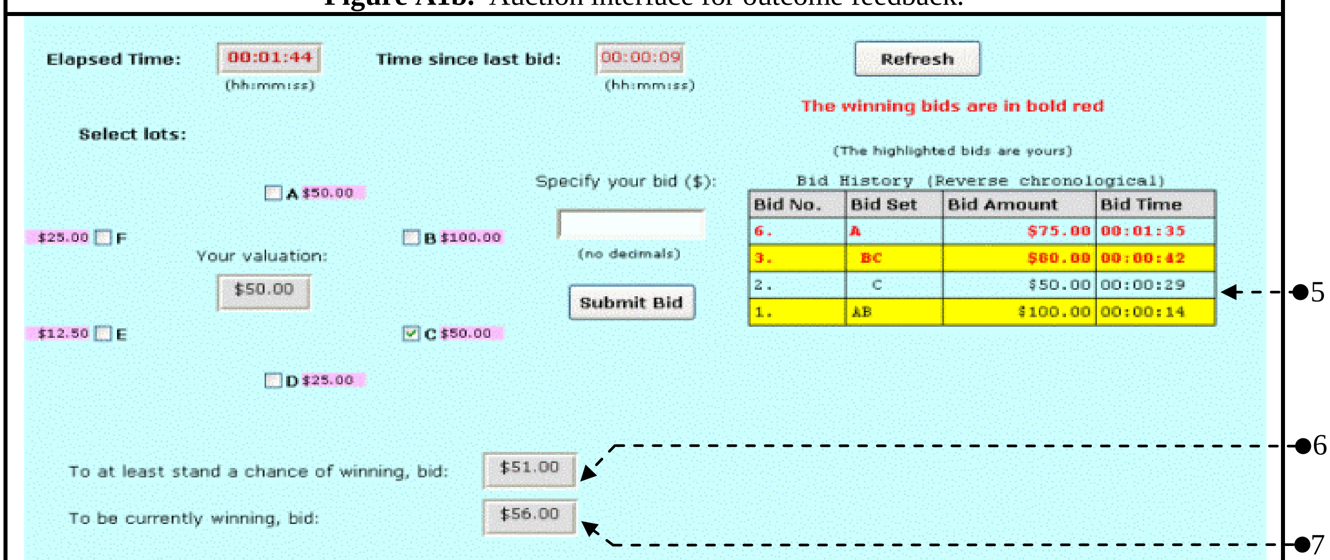

Figure A1c. Auction interface for price feedback.

Appendix A2 – Descriptions of experimental interface marked in Appendix A1.

Number	Description
1	Any individual lot or a combination of lots could be selected by simply clicking on the checkboxes beside each lot. The amounts next to the checkboxes denote the valuations of the individual property lots. These amounts were displayed during the entire course of the auction.
2	This table displayed all the placed bids in the baseline feedback case. All the bids of placed by a particular bidder were highlighted on his/her screen.
3	This label displayed the valuation of the selected individual lot or bundle. The valuation of the bundle {B,C} in this example is $165.00.
4	This table displayed all the placed bids in the outcome feedback case. All the bids of placed by a particular bidder were highlighted on his/her screen as in the baseline case. Furthermore, all the provisionally winning bids were identified in bold red at all stages of the auction.
5	This table displayed all the non-losing bids in the price feedback case. All losing bids were removed from display (e.g., as can be seen from this table, bids 4 and 5 are not displayed). All the bids placed by a particular bidder were highlighted on his/her screen as in the other two cases. Further, all the provisionally winning bids were identified in bold red at all stages of the auction as in outcome feedback case.
6	This label displayed the minimum price for placing a non-losing bid on a chosen bundle. In this example, the current minimum price for placing a non-losing bid on Lot C is $51.00.
7	This label displayed the minimum price for placing a winning bid on a chosen bundle. In this example, the current minimum price for placing a winning bid on Lot C is $56.00.

Appendix B – Survey questions.

All items included a 7-item Likert scale for responses:

1	2	3	4	5	6	7
Strongly disagree	Moderately disagree	Somewhat disagree	Neutral (neither agree nor disagree)	Somewhat agree	Moderately agree	Strongly agree

Constructs and their indicators
Perceived Ease of Use (PEOU)
PEOU1: I found this mechanism understandable for buying or selling multiple items.
PEOU2: I found the software easy to use.
PEOU3: I found the software to be user friendly.
PEOU4: I felt very comfortable using the system.
Perceived Usefulness (PU)
PU1: I found this mechanism suitable for buying or selling multiple items.
PU2: I found this mechanism effective for buying or selling multiple items.
PU3: Using combinatorial auctions for buying or selling multiple items seems like a good idea to me.
PU4: Combinatorial auctions are beneficial for buying or selling multiple items.
Intention of Use (IOU)
IOU1: I will encourage my friends to participate in this type of auction.
[Potential] Usefulness of Price Feedback Components
I found the information provided by the system, [In this auction, if the system provided information] regarding the minimum I needed to bid in order for my bid to be winning, [it would have been] useful in formulating my bids.
I found the information provided by the system [In this auction, if the system provided information] regarding the minimum I needed to bid in order for my bid to stand a chance of winning in the future, [it would have been] useful in formulating my bids.
I found the removal from the bid history, of [In this auction if] the bids that stood no chance of winning in the future [were removed from the bid history], [it would have been] useful in formulating my bids.
Impact – Net Promoter Score (NPS)
I will encourage my friends to participate in this type of auction.

Appendix C - Instructions to subjects

This is an experiment in market decision making, and you will be paid for your participation in cash, at the end of the experiment. Different participants may earn different amounts. What you earn depends on your decisions and on the decisions of others.

The experiment will take place through the computer workstations at which you are seated. It is important that you not talk or in any way try to communicate with other participants during the experiment. If you disobey the rules, we will have to ask you to leave the experiment.

Before the experiment starts, there will be a detailed instruction period. During the instruction period, you will be given a complete description of the experiment. This will be followed by a short test of the basic concepts that you learn in the instructions. Once you leave the instructions and go on to the tests, you will not be able to come back to the instructions. So, please ensure that you have understood all the instructions before leaving them.

If you have any questions during the instruction period, raise your hand and your question will be answered so everyone can hear. If any difficulties arise after the experiment has begun, raise your hand, and an experimenter will come and assist you.

1. Combinatorial Auctions

In this experiment you will participate in a type of auction called a *combinatorial auction*.

A combinatorial auction is an auction in which several different items can be sold at once. In such auctions, bidders are allowed to bid on combinations of items as well as on individual items. For example, if two items A and B are available for auction, you can place bids on the single item {A}, the single item {B}, and the two-item set {AB}. In contrast, a traditional non-combinatorial auction only allows bids on the two items {A} and {B} separately.

2. Determining Winners

The winner in a combinatorial auction is determined by the auctioneer so as to maximize his/her revenue. Table 1 shows an example of bids in a combinatorial auction with 3 items, A, B and C. The bids are shown in reverse chronological order.

Table 1. Winner Determination

Bid Sequence	Bid Sets	Bid Amounts
6.	{A}	**$75**
5.	{BC}	$80
4.	{ABC}	$140
3.	{BC}	**$80**
2.	{C}	$50
1.	{AB}	$100

The winning bids in the above example are the underlined bids, Bid 3 and Bid 6, because these two bids combine to generate the maximum revenue of $155. Since each item can be sold to at most one bidder, no other combination of bids (with non-overlapping item sets) would have generated this much revenue.

Note that if two bidders make the same exact bid (that is, they bid the same amount on the same item set), the bid that is placed later is not considered while determining winners. In the above example, Bid 5 is ignored because it is exactly the same as an earlier bid, namely Bid 3.

3. Determining Winners

In our simulated environment, there are SIX property lots surrounding a lake. You and your fellow participants in this experiment will be competing to buy these lots. The lots are adjoining and successively labeled A through F, so that Lots A and F are also adjoining. This is shown in Figure 1.

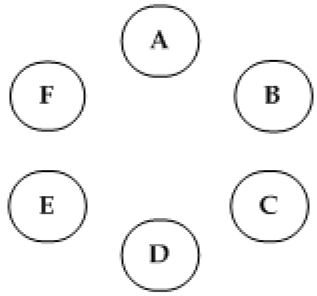

Figure 1. Property Lots

Acquiring two adjoining lots (e.g., {AB}) will have greater value for you than two separated lots (e.g., {AE}) of equal individual values, because adjoining lots afford more options for development.

4. Lot Valuation

In this auction, you have a lot designated as your *preferred lot*. This is the lot with the maximum worth to you. The value of every other lot decreases by 50% as the lot is farther from the preferred position. For example, if Lot B is your preferred lot and its value is $100, then the values of the individual lots will be as shown in Figure 2.

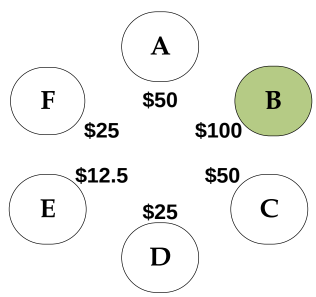

Figure 2. Example of bidder valuations.

Having adjoining lots will increase your combined value of the lots by 10% for every additional adjoining lot. For example, if the individual valuations of the lots are as depicted in Figure 2 above, the values of some of the lot-combinations would be as follows:

Table 2. Super-additive valuations.

	Lots	Adjoining lots	Value
Example 1	{AB}	2 adjoining	(100 + 50) * 1.1 = $165.00
Example 2	{AF}	2 adjoining	(50 + 25) * 1.1 = $82.50
Example 3	{CDE}	3 adjoining	(50 + 25 + 12.5) * 1.2 = $105.00
Example 4	{BEF}	1 separate; 2 adjoining	100 + (12.5 + 25)*1.1 = $141.25

You do not need to remember any of these values as they will be provided to you at all times during the course of the auction.

5. Finding your Valuation

Once the auction starts, your valuations for the individual lots will be displayed on the screen at all times as shown in Figure 3.1. The amounts denote how much each lot is worth to you as mentioned earlier.

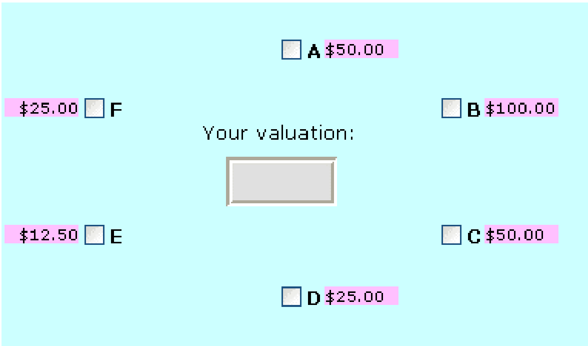

Figure 3.1. Valuation of individual property Lots

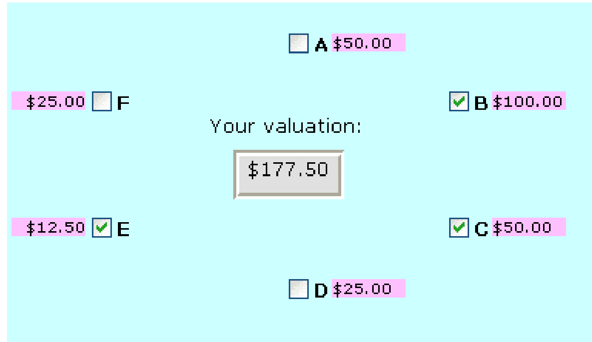

Figure 3.2. Valuation of a combination of property Lots

You can find your valuations for any possible combination of the lots by just clicking on the lots. For example, the valuation of Lots {BCE}can be found by clicking on the checkboxes corresponding to the lots as shown in figure 3.2. You will not know the valuations of the other bidders.

6. Duration of Auction

The auction will last <u>at least 15 minutes</u>. After the first 13 minutes, the auction will end whenever there is no bid placed for 2 minutes. So, for example, if a bid is placed at 14 minutes 30 seconds, the auction will last at least 16 minutes 30 seconds. You will be informed of the beginning and ending of the auction, the elapsed time, as well as the time since the last bid.

7. Placing Bids

A *<u>bid</u>* is the amount of money you are ready to pay for the lots you selected. As mentioned earlier, you can place bids on a single lot as well as a combination of lots. By placing a bid on an item or a combination of items, you express your desire to obtain the item(s) at your given bid-amount. You can place as many bids as you want on as many items you want between the opening and closing of the auction.

Bids can be placed by selecting the lots, entering a bid amount, and then pressing the <submit bid> button. <u>You are only allowed to place integer bids</u>, i.e., no decimals are allowed in the bids you place. You will be able to see your bids as well as the bids placed by other bidders participating in the auction. The bids will be displayed in reverse chronological order with the ones you have placed highlighted on your screen. An example snapshot is shown in Figure 4, where Bids 1 and 3 are your bids.

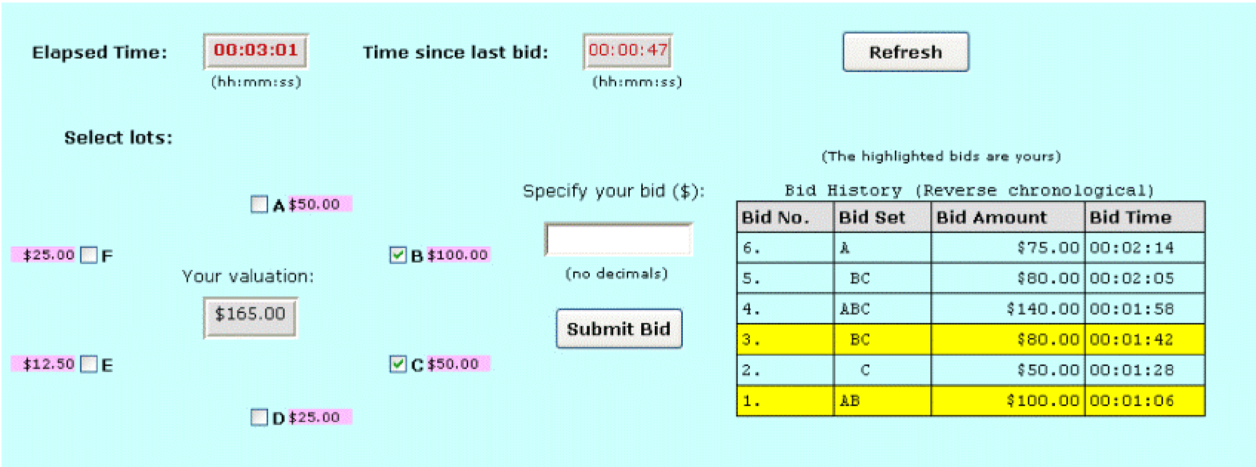

Figure 4. Bid submission and bid history

Note that the elapsed time and the time since last bid will be displayed on the screen but they will not refresh automatically. You will need to refresh the screen using the <refresh> button provided on the screen. In addition, when the auction ends, you can find out that the auction has ended only by refreshing the screen using the <refresh> button. Please do not use the browser's refresh button.

The winners of the auction will be determined at the end of the auction. Depending on the outcome of the auction, you may win none, some, or all of the lots.

8. Bid States

In traditional single item auctions, a bid that is currently losing can never win the auction again. In combinatorial auctions, however, some losing bids can become winning again. We will explain this possibility through an example:

Let's say you have placed a bid of $10 on lot {A} and no one else has placed a bid. Then your bid is currently winning. If a new bid of $11 is placed on lot {AB}, then this new bid becomes winning and your bid of $10 on {A} is losing. However, if a third bid of $2 on {B} comes in, then this new bid makes your bid winning because $10 on {A} plus $2 on {B} make the total revenue on $12, which is greater than $11 placed on {AB}.

Table 3 shows another example to explain this possibility. If the table contains all the bids that have been placed so far in the auction, then the state of each bid after bid 6 is as indicated. Please make sure you understand the states.

Table 3. Example of bid states

Bid sequence	Lots	Bid Value	State of the bid after Bid 6 is placed	Explanation of the state
6.	{A}	**<u>$75</u>**	*Currently winning*	Combined with Bid 3, this bid generates the maximum revenue.
5.	{BC}	$80	*Losing with no chance of winning*	This is exactly same as Bid 3 with bid 3 being placed earlier.
4.	{ABC}	$140	*Losing with no chance of winning*	Combination of Bids 5 and 6 or Bids 1 and 2 or Bids 3 and 6 will always generate more revenue than this bid.
3.	{BC}	**<u>$80</u>**	*Currently winning*	Combined with Bid 6, this bid generates the maximum revenue.
2.	{C}	$50	*Losing but may become winning*	For example, if someone places a bid of $106 on {AB}, this bid will become winning.
1.	{AB}	$100	*Losing but may become winning*	For example, if someone places a bid of $56 on {C}, this bid will become winning

9. Information Feedback (for Treatment 2 only)

At all times during the course of the auction, you will be able to see all the bids that have been placed. In addition, the bids that are *winning* at a given state of the auction will be identified for you in bold red.

Figure 5 shows how the example on the previous page would look on your screen.

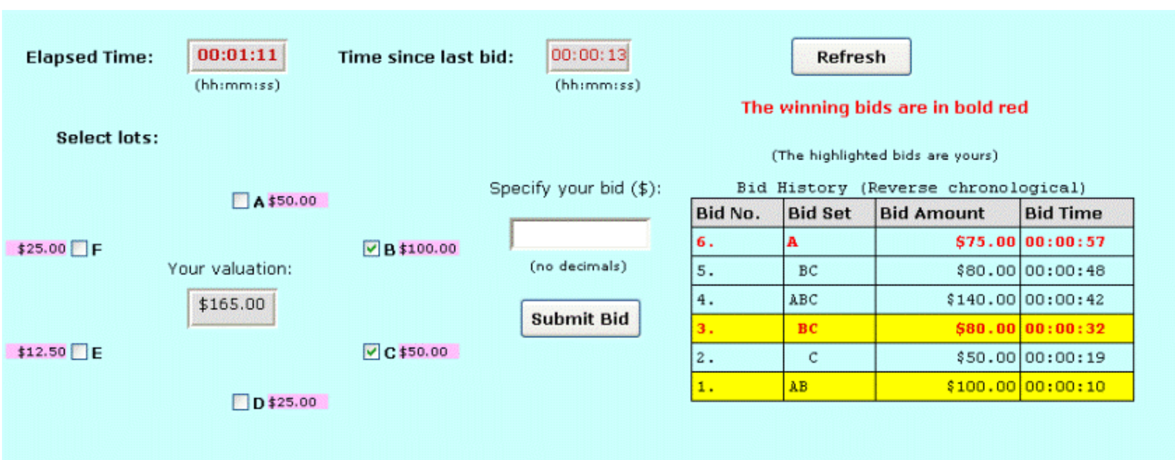

Figure 5. Winning bids at a given auction state

Note that Bids 3 and 6 in the above example are currently winning bids, and so they are in bold red. The bids that are winning may change as new bids are placed.

9. Information Feedback (for Treatment 3 only)

At all times during the course of the auction, you will be able to see all the bids that have been placed. The bids that are *winning* at a given state of the auction will be identified for you in bold red. All bids that stand no chance of winning in the future will be automatically removed from the display. So, you will only be able to see the bids that are either winning or stand a chance of winning in the future. Figure 5 shows how the example on the previous page would look.

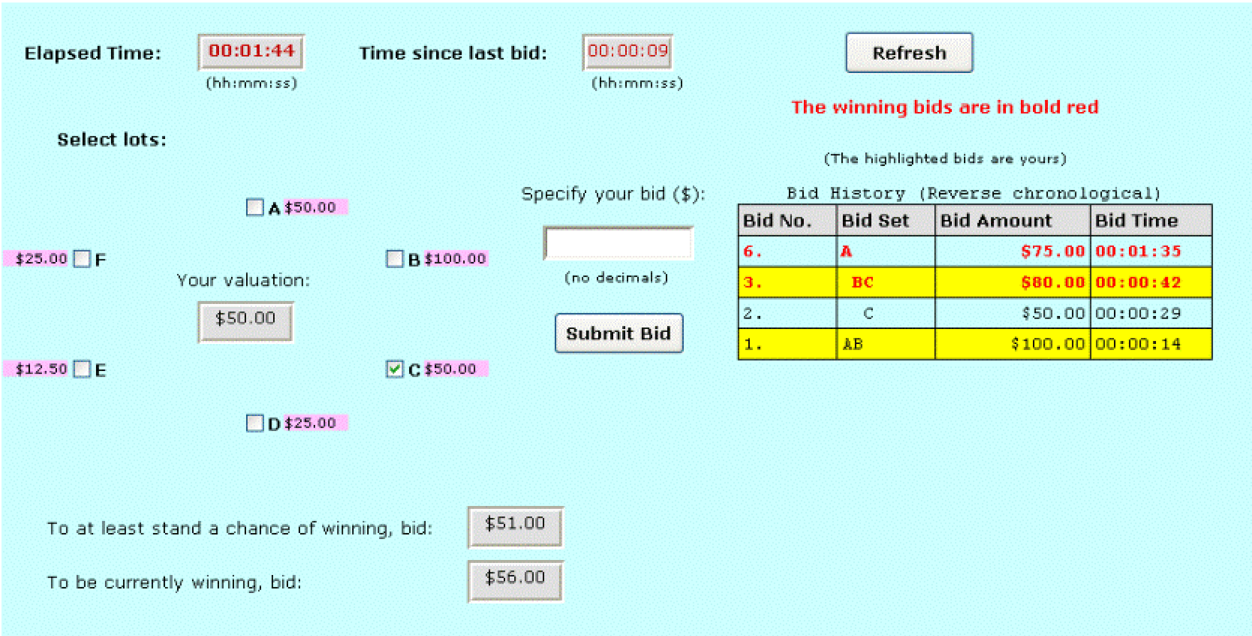

Figure 5. Minimum bid levels

Note that Bids 1 and 2 are currently losing but have a chance of winning, Bids 3 and 6 are currently winning, and Bids 4 and 5 are missing because they are losing with no chance of winning in the future.

When you make a selection of lot(s), in addition to the value of the lot(s) you will also see the following information:

1. The minimum that you need to bid on your selected lots for your bid to at least stand a chance of winning in the future; and
2. The minimum that you need to bid on your selected lots in order to be currently winning.

These values are shown at the bottom left of Figure 5. If you choose to bid on {C}, the minimum that you need to bid in order to stand a chance of winning in the future is $51 . Otherwise, your bid will never be able to win because of the existing bid of $50 on {C}(Bid 2). Similarly, the minimum that you need to bid in order to be winning is $56. Then together with Bid 1, the total revenue will be $156, which is greater than the $155 of Bids 3 and 6 put together.

10. Payoff

You will be paid for the lots you win in proportion to your surplus from the auction. Surplus is the difference between your valuation of the item(s) and your winning bid(s). Consequently, your surplus could be positive, zero or negative depending on whether your winning bid is less than, equal to or greater than your valuation. Table 5 shows some examples of how surplus is calculated.

Table 5. Examples of surplus

	Your valuation	Your Winning Bid	Your Surplus
Lots {AB}	$165.00	$100.00	$65.00
Lots {CDE}	$105.00	$105.00	$0.00
Lots {ABC}	$240.00	$260.00	-$20.00
Lot {D}	$25.00	$100.00	-$75.00

Your participation fee is $10.00. In addition, you will be paid 20 cents for every dollar of your positive surplus. Similarly, you will be charged 20 cents from your participation fee for every dollar of your negative surplus. The maximum amount that might be taken off is your participation fee. You can earn a maximum of $50.00 and a minimum of $0.00. Table 6 shows some examples of payoffs and final earnings.

Table 6. Payoff calculation and final earnings

	Your Surplus	**Your Payoff from the auction**	**Your total earnings(participation fee + payoff from auction)**
Lots {AB}	$65.00	$13.00	$10.00+ $13.00 = $23.00
Lots {CDE}	$0.00	$0.00	$10.00+$0.00 = $10.00
Lots {ABC}	-$20.00	-$4.00	$10.00-$4.00 = $6.00
Lot {D}	-$75.00	-$10.00	$10.00-$10.00 = $0.00

Congratulations! You have completed reading all the instructions. Please feel free to go back to any page you like.