Determining the Optimal Reporting Strategy in Competitive E-Marketplaces

Zeinab Noorian\textsuperscript{1}  Jie Zhang\textsuperscript{2}  Michael Fleming\textsuperscript{1}  Stephen Marsh\textsuperscript{3}
\textsuperscript{1}Faculty of Computer Science, University of New Brunswick, Canada
\textsuperscript{2}School of Computer Engineering, Nanyang Technological University, Singapore
\textsuperscript{3}Communications Research Centre, Canada
Email: z.noorian@unb.ca

Abstract—In a reputation system for multiagent based electronic marketplaces where the number of high quality products provided by good selling agents is unlimited, buying agents often share seller information without the need to consider possible utility loss. However, when those good sellers have limited inventory, buyers may have to be concerned about the possibility of losing the opportunity to do business with the good sellers if the buyers provide truthful information about sellers, due to the competition from other buyers. In this paper, we propose an adaptive mechanism built on a game theoretic basis for buyers to determine their optimal reputation reporting strategy, by modeling both the competency and willingness of other buyers in reporting seller reputation and strategically choosing reporting behaviours that maximize their utility according to the modeling results. The results of the experiments carried out in a simulated competitive e-marketplace confirm that our proposed mechanism leads to better utility for buyers in such an environment.

Keywords—Trust and Reputation, Game Theory, Behavioural Modeling, Seller Selection, Competitive E-Marketplaces

I. INTRODUCTION

In open multiagent based e-marketplaces, some selling agents may be malicious and may not deliver products with the same quality as what they promised. Thus, buying agents need a means to assess the quality of different sellers offering a particular product and select the most profitable seller who best meets the buyers’ requirements. Reputation systems \cite{1}, \cite{2}, \cite{3}, \cite{4} are a particularly effective approach for buyers to model sellers’ reputation (representing their quality) based on the reporting of seller information provided by other buyers (also called advisers). These systems often assume that sellers have infinite (or very large) inventory and the number of high quality products provided by good sellers is unlimited. Also, a successful business transaction of one buyer would not result in a loss for other buyers. Thus, in such environments, buyers can report seller reputation information according to their own endogenous characteristics without considering the possible utility loss as the result of their truthful reporting and competition from others.

However, in certain e-marketplaces, good sellers may have limited inventory. One example is the hotel booking system for a famous tourism area during a peak season since booking a satisfactory hotel is often difficult. Similar marketplaces also include second-hand markets where some used and workable goods (e.g. second-hand textbooks) are often in short supply due to lower prices. Also, different buyers may aim for the same kind of high quality products. These buyers compete to discover the high quality sellers who will maximize their utility in order to conduct business transactions with these sellers before their stock runs out.

In these competitive e-marketplaces, a buyer may have to be concerned about the possibility of losing the opportunity to do business with good sellers if providing truthful reputation information about sellers. To be more specific, after some successful transactions with a seller, if the buyer provides truthful (positive) feedback about the good seller, the buyer may lose the chance to do business with the seller in the future, due to the limited inventory the seller has and the fact that other buyers will also do business with this good seller. If the transactions are unsuccessful, reporting truthful (negative) feedback may cause the buyer to lose the chance to do business with other good sellers because other buyers will not do business with the bad seller but with the other good sellers, after taking the buyer’s advice. In this sense, it is better for buyers not to truthfully reveal seller reputation. On the other hand, buyers are also motivated to participate in information exchange because truthful sharing of seller reputation allows for faster discovery of high quality sellers. It is thus not trivial to determine an optimal reporting strategy for buyers that maximizes their utility in competitive e-marketplaces, and this issue has not yet been well addressed in the literature.

Based on the above discussions, we intuit that other buyers (advisers) may not behave as expected in competitive e-marketplaces. That is, the reporting behaviour of the advisers may not only be dependent on their endogenous characteristics (i.e. competency), because competent advisers may not always be willing to cooperate with buyers by reporting truthful reputation information about sellers. Thus, when choosing their reporting behaviour, buyers should carefully examine the trustworthiness (quality) of advisers in reporting seller reputation information, by also taking into account the willingness of advisers. In additions, buyers should have in mind both possible competition and provision of valuable seller information from advisers. Therefore, in this paper,
we propose an adaptive mechanism for buyers to determine their optimal reporting strategy. Our mechanism is built on a game theoretic basis, enabling buyers to establish a balance between the possibility of losing business opportunities because of truthful reporting and the possibility of not receiving truthful seller information from advisers if the buyers report untruthfully. In the mechanism, buyers not only model the competency of advisers in reporting seller information, but also advisers’ willingness in sharing the information. Based on the modeling results, the buyers choose the reporting behaviour that maximizes their utility. Our mechanism thus provides buyers a means to strategically determine their reporting behaviour.

We also develop a simulation framework to examine the effectiveness of the proposed mechanism in a competitive e-marketplace environment. We measure the utility of different buyers with various reporting behaviours confronting different types of sellers with varying behavioural patterns. We observe that the utility of buyers with strategic reporting behaviours surpass as they can have a better chance of transacting with more profitable/trustworthy sellers. The experimental results also demonstrate that the novel modeling of advisers’ willingness in our mechanism is particularly valuable in helping buyers to gain better utility.

The rest of the paper is organized as follows: the related work is presented in Section II; Section III introduces buyers’ different reporting strategies on the basis of a game theoretic approach and explains the process of modeling advisers’ competency and willingness values. In Section IV, we present the simulation framework and environmental settings in great detail. Experimental results which indicate the efficacy of the proposed mechanism are described in Section V. Finally, we conclude the current work and propose future research in Section VI.

II. RELATED WORK

In Jurca’s thesis [5], he proposed a side payment mechanism to provide incentives for buyers (advisers) to report truthfully by offering honest advisers some extra utility. In this work, he also raised the concern that reporting truthfully may cause some cost to advisers. However, he did not study this issue further in competitive e-marketplaces where the cost of losing business opportunities because of truthful reporting cannot be simply ignored in the design of an incentive mechanism. The trust-based incentive mechanism proposed in [6] also tries to create incentives for advisers to report truthfully by offering honest buyers greater discount from sellers. The basic idea is that, since an honest buyer is most likely the neighbour of many other buyers, if a particular seller gives a discount to the honest buyer, the buyer can promote the seller by propagating the information about the seller to its social network (those other buyers). In this way, the seller would be able to attract more buyers with whom to do business in the future. However, in general, both the side payment and trust-based incentive mechanisms do not consider the case where buyers should also be concerned about other buyers’ reporting behaviours in order for them to optimally decide theirs.

We argue that buyers in competitive e-marketplace environments should strategically determine their reporting behaviours by modeling the trustworthiness (reporting behaviours) of their advisers. Several approaches have been proposed to evaluate the trustworthiness of advisers. For example, in TRAVOS [2], advisers share the history of their interactions with sellers in a tuple that contains the frequency of successful and unsuccessful interaction results. Buyers calculate the probability based on a beta distribution that a particular adviser provides accurate reports given the adviser’s past reports. They then proportionately adjust the trustworthiness of the adviser in giving the current reports. Noorian et al. [7] introduced a two-layered filtering algorithm which aggregates several parameters in deriving the trustworthiness of advisers. In addition to the similarity degree of advisers’ opinions compared to buyers’, this algorithm also considers advisers’ other endogenous characteristics such as optimism, pessimism and realism. These existing trust models, however, do not consider the willingness of advisers in providing truthful information about sellers, because these models were proposed for e-marketplaces with infinite (or very large) inventories of high quality products. These models assume that advisers consistently behave according to their degree of credibility and those other endogenous characteristics. However, in competitive marketplaces, credible advisers might adopt different reporting behaviours despite their dispositions. Therefore, in our mechanism, we also allow buyers to model the willingness of advisers so as to dynamically determine the trustworthiness of advisers’ reports when deciding the buyers’ own reporting strategies.

III. DETERMINATION OF REPORTING STRATEGY

In this section, we present our adaptive mechanism by first introducing its game theoretic basis and then describing how buyers should model the trustworthiness of other buyers by considering both their competency and willingness.

A. Game Theoretic Basis

As mentioned in Section I, buyers in a competitive e-marketplace must make a trade-off between the probability of losing opportunities to do business with good sellers because of their truthful reporting and the probability of not being able to quickly discover good sellers if they always report untruthfully about sellers. One possible reporting strategy is that a credible buyer provides spurious reports despite their dispositions so as to mislead others and prevent them from transacting with the best sellers. The second strategy is that a credible buyer might opt to behave based on
her endogenous behavioural characteristics and constantly provide truthful information regardless of reporting strategies adopted by others. Clearly in both cases, such buyers cannot achieve the largest utility in the long run. The buyers adopting the first strategy will not be able to gain truthful information about sellers for quickly discovering trustworthy sellers. The buyers adopting the second strategy will lose opportunities to do business with good sellers because of competition from other buyers.

Given these arguments, we claim that buyers should be provided with a mechanism to strategically determine their reporting behaviours. Our proposed mechanism is based on the well known game theoretic concept, the Prisoner’s Dilemma (PD) game. As such, buyers evaluate the expected payoff they can obtain for adopting different reporting behaviours and select the one which yields the largest payoff.

Theoretically speaking, in a PD game, if two strategic buyers cooperate by providing each other truthful seller reputation information, each buyer will then gain a certain unit of reward $R$ for mutual cooperation, while if they both defect by providing untruthful information they will receive punishment $P$ for mutual defection. Finally, if one buyer cooperates and the other defects, the defector gains $T$ which represents the defector’s desire to betray and the cooperator receives $K$ which is the sucker’s payoff. The base payoff matrix for the PD game is shown in Table I.

<table>
<thead>
<tr>
<th>Agent 1</th>
<th>Cooperate</th>
<th>Defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooperate</td>
<td>$R$</td>
<td>$K$</td>
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<tr>
<td>Defect</td>
<td>$T$</td>
<td>$P$</td>
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Table I: Prisoner’s Dilemma payoff matrix

Similar to the PD principles, in competitive marketplaces, if buyers intend to exchange seller reputation information for only a few rounds, the dominant strategy for both buyers is to defect. However, if a buyer wants to operate for a long period of time, the buyer may choose cooperation and accept the probability of lower payoff during the first round to increase the probability that partners will also cooperate with the buyer in future rounds. We thus calculate the expected payoff of buyers for continuing mutual cooperation, i.e. exposing truthful reputation information, inspired by the idea presented in [8] as follows:

$$U_C = V_p * R + \min(\gamma_b, \gamma_a) * \frac{R}{1 - \min(\gamma_b, \gamma_a)}$$ (1)

where $V_p$ represents the importance degree of the interaction partner. $\gamma_b = 1 - \gamma_b$ and $\gamma_a = 1 - \gamma_a$ are the factors in $[0, 1]$ discounting the expected payoff obtained in the future through the cooperative action between buyers, implying that it is preferable to obtain a payoff in the current interaction rather than in future interactions. $\gamma_a$ and $\gamma_b$ indicate the age of the two buyers respectively, i.e. the duration that the two buyers have been in the e-marketplace maintained by the central server. Each buyer has a certain purchase mission which will be started right after the buyer joined the marketplace. We conjecture that as the duration of buyers increases, they would be closer to finish their missions and leave the marketplace. Therefore, the possible future opportunity of interacting with each other decreases proportionately. If either of $\gamma_b = 1 - \gamma_b$ or $\gamma_a = 1 - \gamma_a$ is very small, the promise of future payoffs is not sufficient to encourage the buyers’ cooperative behaviour.

Similarly, the expected payoff of the buyers with defection action (i.e. reporting untruthful seller reputation information) can be computed as follows:

$$U_D = \frac{1}{V_p} * T + \min(\gamma_b, \gamma_a) * \frac{P}{1 - \min(\gamma_b, \gamma_a)}$$ (2)

From Equation 2, it is noticeable that in our mechanism, a strategic buyer calculates the payoff of defection behaviour by assuming that interaction partners adopt a “Grim” strategy (the most unforgiving strategy) for the next rounds of the game when the interaction partners detect the buyer’s defection behaviour, despite the variety in the partners’ reporting behaviours and their liberty to adopt different reporting strategies. Based on the Grim strategy, a buyer will also initiate an interaction with the cooperation behaviour. However, a single defect by the interaction partner will trigger defection from the buyer forever.

To formalize the importance degree of the interaction partner (as used in both Equations 1 and 2), we further define a distribution of $V_p(Tr) = -\log(1 - Tr)$ where $Tr$ represents the trustworthiness of the partner (adviser), which will be formalized in the next section. Figure 1 illustrates this distribution more clearly. Using this distribution, buyers appreciate those partners with high trustworthiness by adopting cooperative attitudes in their interactions.

### B. Modeling the Trustworthiness of Advisers

In our mechanism, buyers model the trustworthiness of other buyers (called advisers). The results will be used for
determining the buyers’ reporting strategies (Equations 1 and 2). The trustworthiness assessment of advisers is attributed to two constituents: 1) the competency of advisers, which signifies the credibility/honesty of advisers; 2) the willingness of advisers, which captures the attitudes that advisers adopt in truthfully reporting their information. The key idea is that a competent adviser may not always be willing to cooperate with the buyer by reporting truthful reputation information about sellers unless the adviser makes sure that the buyer would have a trustworthy attitude towards the adviser once a request is made.

The trustworthiness of an adviser \( A_i \), where \( A_i \in A = \{A_1, A_2, \ldots, A_n\} \), is then calculated as follows:

\[
Tr(A_i) = Comp(A_i) \times Will(A_i)
\]

(3)

Here, \( Comp(A_i) \in [0, 1] \) is the competency of adviser \( A_i \) in reporting accurate seller information, and \( Will(A_i) \in [0, 1] \) is the willingness of \( A_i \) in truthfully reporting seller information. We will describe the modeling of these two factors in the next two sections.

1) Modeling the Competency of Advisers: Suppose that a buyer \( B \) sends a query to advisers requesting information about sellers \( S = \{S_1, S_2, \ldots, S_j, \ldots, S_m\} \) on the outcomes of the interactions between the advisers and sellers occurring within a time threshold \( t \) (which diminishes the risk of changeability in sellers’ behaviour). Adviser \( A_i \) responds by providing a rating vector \( R_{(A_i, S_j)} \) for each seller, for example \( S_j \). It contains a tuple \( (r, s) \) which indicates the number of successful \( r \) and unsuccessful \( s \) interaction outcomes with seller \( S_j \) respectively. Once the evidence is received, for each \( R_{(A_i, S_j)} \), buyer \( B \) calculates the expected value of the probability of a positive outcome \( pr_r \) for seller \( S_j \) based on a beta distribution [1] as follows:

\[
E(pr_r, S_j)_{A_i} = \frac{r + 1}{r + s + 2}
\]

(4)

Clearly, \( 0 < E(pr_r, S_j)_{A_i} < 1 \) and as it approaches 0 or 1, it indicates unanimity in the body of evidence [9]. That is, particularly large values of \( s \) or \( r \) provide better intuition about an overall tendency and quality of sellers. In contrast, \( E(pr_r, S_j)_{A_i} = 0.5 \), (i.e., \( r = s \)) signifies the maximal conflict in gathered evidence, resulting in increasing the uncertainty in determining the quality of sellers. Based on these intuitions, we are able to calculate the degree of reliability and certainty of ratings provided by advisers. More formally, let \( x \) represent the probability of a successful outcome for a certain seller. Based on the Definitions (2) and (3) in [9], the reliability degree of each \( R_{(A_i, S_j)} \) can be defined as follows:

\[
C(r, s)_{A_i} = \frac{1}{2} \int_0^1 \frac{x^r(1-x)^s}{\int_0^1 x^r(1-x)^s \, dx} - 1 \, \, dx
\]

(5)

Following [9], reliability is a minimum when \( E(pr_r, S_j)_{A_i} = 0.5 \). As such, the less conflict in their ratings, the more reliable the advisers would be. However, buyer \( B \) should not strictly judge the advisers with rather low reliability in their \( R_{(A_i, S_j)} \) as deceptive advisers since this reliability factor could signify both the dishonesty of advisers and the dynamic and fraudulent behaviour of sellers reported by the advisers. For example, some malicious sellers may provide satisfactory quality of services in some situations when there is not much at stake and act conversely in other occasions associated with a large gain.

To address this ambiguity, buyer \( B \) computes \( E(pr_r, S_j)_{B} \) in her personal experience, \( R_{(B, S_j)} \), with a set of sellers \( S_{B,A_i} \), with whom the advisers also have experience.1 Through the comparison of advisers’ metrics with the buyer’s own, the buyer would have more trust in those advisers with a similar rating pattern and satisfactory level of honesty. More formally, buyer \( B \) measures an average level of dishonesty of \( A_i \) by:

\[
\bar{D}(A_i) = \sum_{j=1}^{\left|S_{B,A_i}\right|} \left| E(pr_r, S_j)_{B} - E(pr_r, S_j)_{A_i} \right| \left|S_{B,A_i}\right|
\]

(6)

It may also happen that an honest adviser lacks experience with sellers. Thus, despite her inherent honesty, her reliability degree is low and she should not be highly trusted. To address this, we introduce an uncertainty function \( \overline{U}(A_i) \) to capture the intuition of information imbalance between \( B \) and \( A_i \) as follows:

\[
\overline{U}(A_i) = \frac{\left|S_{B,A_i}\right| - \left|C(r, s)_{B} - C(r, s)_{A_i}\right|_{S_j}}{\left|S_{B,A_i}\right|}
\]

(7)

The competency degree of \( A_i \) is then calculated by reducing her honesty based on her certainty degree as follows:

\[
Comp(A_i) = \left(1 - \overline{D}(A_i)\right) \times \left(1 - \overline{U}(A_i)\right)
\]

(8)

2) Modeling the Willingness of Advisers: In our mechanism, the strategic buyer \( B \) mathematically formulates the willingness of an adviser \( A_i \) considering two factors: 1) the difference between the adviser’s opinions, \( r(A_i) \), and the mean value of the ratings provided by all advisers and the buyer \( B \); 2) the degree of honesty, \( HD_{(B,A_i)} \), of the buyer \( B \) in revealing the reputation information to adviser \( A_i \) which is the ratio of the number of truthful ratings to the total number of ratings provided to \( A_i \), as follows:

\[
Will(A_i) = HD_{(B,A_i)} \times e^{-Dev(A_i)}
\]

(9)

\[
Dev(A_i) = \int_{-Dev(A_i)+\mu}^{\mu} e^x \, dx 
\]

where \( \mu \) indicates the mean value of the provided ratings by all advisers and the buyer \( B \). Note that the strategic buyer

\[\text{Here, we choose a set of sellers } S_{B,A_i} \subset S \text{ with whom buyer } B \text{ has sufficient experience, to make sure that the buyer has sufficient knowledge to judge the advisers.}\]
initially assumes that advisers provide ratings according to their endogenous behavioural characteristics evaluated as the competency in the previous section, and thus adjusts $Will_{(A_i)} = 1$ for all advisers. However, as time progresses, the strategic buyer learns advisers’ attitudes and updates their willingness accordingly.

Similar to the method for calculating competency, the buyer takes into account the differences of the behavioural dispositions of advisers and would not degrade advisers’ willingness unless the advisers’ ratings significantly diverge from $\mu$ in certain circumstances. More formally, given the expected interaction outcome, $Exp(S_{ij})$, and the actual outcome, $Act(S_{ij})$, of the buyer with a seller $S_i$, the willingness of advisor $A_i$ would be updated using Equation 9 under the following conditions:

$$Act(S_{ij}) > Exp(S_{ij}) : \begin{cases} r_{(A_i)} < \mu - \sigma & \sigma < \mu \land \frac{\sigma}{\mu} > \eta \\ r_{(A_i)} < \mu & \sigma < \mu \land \frac{\sigma}{\mu} > \eta \end{cases}$$ (10)

$$Act(S_{ij}) < (1 - \epsilon) \times Exp(S_{ij}) : \begin{cases} r_{(A_i)} > \mu - \sigma & \sigma < \mu \land \frac{\sigma}{\mu} < \eta \\ r_{(A_i)} > \mu & \sigma < \mu \land \frac{\sigma}{\mu} < \eta \end{cases}$$ (11)

To explain, in the case where $Act(S_{ij})$ surpasses $Exp(S_{ij})$, a strategic buyer updates those advisers whose ratings are significantly below $\mu$. In Equation 10, $\eta$ represents an acceptable level of dispersion in advisers’ feedback. We calculate the ratio of $\sigma$ (the standard deviation of the provided ratings) and $\mu$ as the coefficient of variation, which articulates the quality of dispersion of the provided ratings. As $\sigma/\mu$ approaches 1, it shows a bad dispersion of the rating reports which is an indication of an environmental circumstance in which almost half of the advisers act honestly and the rest act maliciously with a complementary pattern of cheating [10]. Through proper adjustment of $\eta$, buyers are able to detect advisers with dishonest reporting behaviour and degrade their willingness values appropriately.

On the contrary, if the actual transaction outcome is lower than the predicted value, i.e. $Act(S_{ij}) < (1 - \epsilon) \times Exp(S_{ij})$, a strategic buyer adjusts the willingness of advisers whose ratings are around $\mu$. In Equation 11, the situation with $\sigma/\mu < \eta$ implies an environmental condition where a majority of advisers mislead buyers to inaccurately assess the quality of sellers by reporting exaggeratedly incorrectly-positive feedback regarding queried sellers. In contrast, since $\sigma/\mu > \eta$ represents the condition where the distribution of honest and dishonest advisers is rather balanced in the e-marketplace, our mechanism reduces the willingness of those advisers whose ratings are greater than $\mu$. Note that, through introducing $\epsilon$, we give strategic buyers the flexibility to adaptively determine the acceptable margin of differences between $Act(S_{ij})$ and $Exp(S_{ij})$ pertaining to their own behavioural patterns and environmental conditions.

IV. SIMULATION FRAMEWORK

In this section, we introduce a simulation framework for conducting experiments to compare the efficacy of different buyers with various reporting strategies after transacting with sellers. The e-marketplace environment used for experiments is populated with self-interested buyers and sellers and is operated for 30 days. In such a competitive e-marketplace, there are 6 sellers in total, and they have a set of goals of making purchases of 30 different products by the end of the game. Sellers have limited inventory and supply their products with different quality of service (QoS). We assume the existence of 360 sellers where 50% of them are honest. Each product is offered by 12 sellers; half of them are honest and their QoS value of each attribute (i.e. $V_{ij}$) in the latter equations) varies from $[0.5, 0.95]$ and half of them are dishonest with the QoS within $[0.1, 0.4]$. We can see that the number of high quality products is much smaller than the amount of buyers’ demand. In general, only around 50% of buyers will be satisfied by high quality products. In this case, buyers will have to compete to purchase those high quality products. The QoS of a product provided by the honest sellers differs a little from their reported QoS by a value chosen from a normal distribution $N(0.15, 0.02)$. On the other hand, dishonest sellers have actual QoS values that differ much from their reported values by a number chosen from the normal distribution $N(0.05, 0.02)$.

Buyers compete to increase their revenue by transacting with honest sellers who hold high quality products. They evaluate the trustworthiness of different sellers and select ones who maximize their profit. The buyers and sellers are brought together by a reputation-aware multi-attribute First Score Sealed Bid Procurement (FSSBP) auction [11], where the auctioneer is a buyer and bidders are sellers. The auction is run by each buyer. Each buyer determines the winning seller based on the optimized combination of the seller’s trustworthiness, QoS attribute values and offered price that provides the highest profit to the buyer.

Assume the scenario where a buyer $B$ intends to purchase a product $p$. The buyer will first limit the sellers considered for the auction, by modeling their trustworthiness. Next, $B$ announces the list of negotiable attributes and her preferences concerning the requested product’s QoS attributes, and invites potential sellers to submit their multidimensional bids on the attributes. Sellers submit their bids according to the dominant bidding strategy [11]. Afterwards, $B$ assesses the submitted bids, ranks them according to her preferences on the attributes and designates a contract to the seller who maximizes her utility. More details about the formulation and each procedure of the FSSBP auction are given in the rest of this section.

First of all, similar to the approaches proposed in [1], [2], [6], the trustworthiness of sellers can be computed by combining buyers’ own information about the sellers based on their previous interactions as well as the information shared by advisers. Information shared by advisers will be discounted according to the trustworthiness of the advisers modeled using the method proposed in the previous section.
Also, buyer $B$’s utility $U(B)$ is formalized as follows:

$$U(B) = Q(S_j) - P(S_j)$$  \hspace{1cm} (12)

$$Q(S_j) = Tr(S_j) \times F(S_j)$$

$$F(S_j) = \sum_{i=1}^{m} \omega_i \times V_i(S_j)$$

The utility of $B$ depends not only on the price a seller $S_j$ charges $B$ for the particular product $(P(S_j))$, but also relates to the quality of the seller’s product $(Q(S_j))$. If we consider $m$ arbitrary attributes for the product provided by $S_j$, $Q(S_j)$ can be computed based on the quality value of each QoS attribute $i$ that $S_j$ claims to fulfill, $V_i(S_j)$, given $B$’s preferences $(\omega_i)$ where $i \in \{1...m\}$. Note that buyers are assumed to have the same valuation on the same attribute value, but different weights on different QoS attributes. Buyer $B$ captures the uncertainty characteristics of the e-marketplace and discounts the claims of sellers based on their trustworthiness $Tr(S_j)$ in delivering their previous commitments.

In the proposed simulation framework, buyers announce their preferences over different attributes using the scoring function as follows:

$$S(B) = -C(S_j) + \sum_{i=1}^{m} W_i \times V_i(S_j)$$  \hspace{1cm} (13)

where $W_i$ are the weights that $B$ assigns to attribute $i$. Note that the values of the weights $W_i$ could be equal to or different from the actual weights $\omega_i$ that $B$ considers for its negotiating attributes.

Here, buyers arbitrarily alter the weights of their preferences in order to show their leaning towards different attributes without revealing their actual preferences. As such, buyers would initialize $W$ subjectively depending on the importance of each particular attribute in their perspective.

According to Theorem 1 in [11], [12], for $n$ sellers, given the buyers’ actual weights $\omega_i$ and the distribution of the sellers’ cost parameter $\bar{\theta}$, buyer $B$ would formulate the optimal value for $W_i$ in the proposed FSSBP auction protocol as follows:

$$W_i(\bar{\theta}) = \frac{\omega_i \times \int_{\bar{\theta}}^{\theta} \frac{(\bar{\theta} - t)^{n-1}}{t} dt}{\int_{\bar{\theta}}^{\theta} \frac{(\bar{\theta} - t)^{n-1}}{t} dt + \int_{\bar{\theta}}^{\theta} \frac{(\bar{\theta} - z)^{n-1}}{z} dz dt}$$  \hspace{1cm} (14)

Besides, sellers propose their bids as a combination of multiple quality attributes and their price parameters, considering their own cost parameters and the buyers’ preferences. If the seller $S_j$ is aware of the number of competitors $n$ and the cost parameters uniformly distributed in $[\bar{\theta}, \theta]$, the dominant bidding strategy for $S_j$ based on its cost parameter $\theta$ would be calculated as [11], [13]:

$$V_i^*(S_j) = \left(\frac{W_i}{2\theta}\right)^2$$  \hspace{1cm} (15)

where $i \in \{1...m\}$ and

$$C(S_j) = \sum_{i=1}^{m} W_i^2 \times \frac{1}{4\theta} \times \frac{1}{\theta^{n-1}} \int_{\theta}^{\bar{\theta}} \frac{(\bar{\theta} - t)^{n-1}}{t^2} dt$$  \hspace{1cm} (16)

In this simulation framework, we set some parameters for latter experiments. We randomly select the value of $\gamma_a$ and $\gamma_b$ used in Section III-A from the normal distribution $N(0.05, 0.01)$ for different buyers. We also set the threshold $\eta$ in Equation 15 to be 0.7 and $\epsilon$ used in Section III-B2 to be 0.1. We also run experiments with different possible values for those parameters and obtain similar results, as the purpose of the experiments is to simply show that our proposed adaptive mechanism is beneficial.

V. EXPERIMENTAL RESULTS

We have designed a series of experiments to evaluate the performance of buyers in the competitive e-marketplace when they adopt different reporting strategies. These experiments underline that behaviours of buyers in reporting seller reputation information should be adaptively adjusted according to our proposed mechanism, in order to achieve the best possible outcomes. We also conduct experiments to show that considering the willingness factor when modeling the trustworthiness of advisers helps buyers find more trustworthy sellers and in consequence gain better utility.

Figure 2: The profit of different types of buyers

In the first set of experiments we articulate that adopting honest attitudes would not always lead to the optimum outcome, specifically in a competitive marketplace. Instead, by acting strategically and through modeling the willingness of even the most competent advisers, buyers would be able to find the best possible sellers. In these experiments, we consider three types of buyers, 2 buyers for each type: 1) ALLC: the competent buyer with cooperative attitude, who always provides truthful information about seller reputation; 2) ALLD: the competent buyer with defective attitude, who always provides untruthful information about seller reputation; 3) trust-strategic buyer, who strategically decides the quality of reported seller reputation information based on

2The buyers adopting the ALLC and ALLD strategies only model the competency of advisers, that is $Tr(A_1) = Conv(A_1)$. 
our proposed mechanism. In these experiments we assume that sellers do not change their behaviors when transacting with different buyers in this e-marketplace. Thus, the time threshold \( t \) is set to \( \infty \) in this case.

In Figure 2, we notice that buyers with the ALLD strategy surpass others in the first few rounds as they receive accurate seller reputation information from others but send distorted information in return. However, trust-strategic buyers would analyze and learn their behaviors as time passes and adopt an appropriate strategy to encounter ALLD buyers properly. Our mechanism provides such buyers with the ability to obtain maximum profits in comparison to their rivals. In this experiment we also notice that ALLC buyers who blindly share truthful information will gain the worst profit in such a competitive e-marketplace.

In Figure 3, we demonstrate the average trustworthiness of sellers with whom the different types of buyers have done business. It indicates that the buyers adopting the proposed trust strategy can discover a significantly larger number of more trustworthy sellers to do business with.

Figure 4 shows the accuracy of trust-strategic buyers in predicting the expected utility of doing business with sellers. We notice that our mechanism enables such buyers to have more accurate predictions on the QoS of the products provided by their transaction partners in the future, in comparison with the other types of buyers. As such, the deviation of the actual profit and the expected utility of sellers is minimum for the trust-strategic buyers.

In the second set of experiments, we first evaluate the accuracy of the modeling of the advisers’ willingness by comparing the modeling results against the pre-defined willingness of advisers. Considering the genuine willingness of buyers adopting the ALLC and ALLD strategies as 1 and 0, respectively, and the willingness of the trust-strategic buyer as 1 when \( U_C \geq U_D \) and 0 otherwise, we calculate the Mean Square Error (MSE) of the trust-strategic buyer in predicting the actual willingness of advisers. The results are shown in Figure 5. The trust-strategic buyer initially assumes that the willingness of advisers are equal to 1 (thus MSE > 0) in the first few days. As time progresses, the buyer will learn and adjust the advisers’ willingness adaptively so that MSE \( \approx 0 \). Note that the bumping point (day four) depicts the sudden change in the willingness of trust-strategic advisers from 1 to 0, implying that the cooperation payoff of advisers drops below their defection payoff (\( U_C < U_D \)). We notice that the trust-strategic buyer is provided with a mechanism to capture such changes and apply an appropriate update to the willingness of advisers in the next days.

To evaluate the value of modeling the willingness of...
advisers in addition to their competency, we compute the expected profit of a group of trust-strategic buyers with the modeling of the willingness factor (using Equation 3) versus trust-strategic buyers without the modeling of willingness (i.e. Equation 3 is changed to $Tr(A_i) = Comp(A_i)$). From Figure 6, we can see that the obtained utility of the former group of buyers is significantly higher than the latter group who do not consider the willingness of advisers in determining their reporting strategy. This clearly indicates the necessity of integrating the willingness of advisers in the competitive marketplace where advisers might behave maliciously despite their good competency.

![Figure 7: The effect of the willingness factor in discovering high-quality sellers](image)

Figure 7: The effect of the willingness factor in discovering high-quality sellers

In Figure 7, we illustrate that the trust-strategic buyer with the ability to model the willingness of advisers is able to find a larger number of sellers with higher trustworthiness to conduct transactions with.

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed an adaptive mechanism for buyers in competitive e-marketplaces to strategically determine their reporting behaviours, regardless of their dispositions, but rather based on the trustworthiness of their advisers as well as the future opportunity of reliance on the advisers’ information about seller reputation. More specifically, in our mechanism, buyers are engaged in variable-length iterated Prisoner’s Dilemma games. Buyers acquire reputation information regarding certain sellers from advisers and evaluate the quality of the received information through the modeling of advisers’ willingness and competency levels. Based on the modeling results, buyers predict the expected utility when taking different reporting behaviours and choose the one that maximizes the utility. We also carried out experiments to verify that our proposed mechanism provides a means for buyers to determine their optimal reporting strategy and achieve better utility. Experimental results also confirm the value of the modeling of advisers’ willingness.

For future work, we will study how to create incentives for buyers to truthfully report seller reputation information in competitive e-marketplaces when our proposed mechanism is employed by the buyers.

REFERENCES


