Auton Agent Multi-Agent Syst
DOI 10.1007/s10458-013-9243-z

Trust-oriented buyer strategies for seller reporting and selection in competitive electronic marketplaces

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Abstract In competitive electronic marketplaces where some selling agents may be dishonest and quality products offered by good sellers are limited, selecting the most profitable sellers as transaction partners is challenging, especially when buying agents lack personal experience with sellers. Reputation systems help buyers to select sellers by aggregating seller information reported by other buyers (called advisers). However, in such competitive marketplaces, buyers may also be concerned about the possibility of losing business opportunities with good sellers if they report truthful seller information. In this paper, we propose a trust-oriented mechanism built on a game theoretic basis for buyers to: (1) determine an optimal seller reporting strategy, by modeling the trustworthiness (competency and willingness) of advisers in reporting seller information; (2) discover sellers who maximize their profit by modeling the trustworthiness of sellers and considering the buyers' preferences on product quality. Experimental results confirm that competitive marketplaces operating with our mechanism lead to better profit for buyers and create incentives for seller honesty.

Keywords Trust and reputation · Competitive e-marketplaces · Trust-strategic · Seller selection · Auction

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Published online: 19 November 2013

1 Introduction

In open multiagent based e-marketplaces, some selling agents may be malicious and may not deliver products of the same quality that they originally 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 [8,9,11,16] are particularly effective approaches for buyers to evaluate sellers. In such systems, if a certain buyer does not have adequate personal experience of some candidate sellers, he will disseminate queries to other buyers (also called advisers) to request information about the sellers. Based on the reporting of seller information provided by the advisers, the buyer can then model the reputation of the sellers. However, in such open environments, advisers may untruthfully report information about seller reputation, if their internal dispositions are deceitful or malicious.

Different approaches [14,20,27] have been proposed to cope with the untruthful reporting problem by modeling the trustworthiness of advisers. These approaches often assume that sellers have infinite (or very large) inventory and the number of high quality products provided by good sellers is unlimited. Furthermore, 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 caused by their truthful reporting and competition from others. In consequence, those approaches model the trustworthiness of advisers based only on their internal characteristics.

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, when 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. In such marketplaces, 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 is not only dependent on their endogenous characteristics (i.e., competency), as competent advisers may not always be willing to cooperate with buyers by reporting truthful reputation information about sellers. Thus, buyers should carefully examine not only the trustworthiness (quality) of advisers in reporting seller reputation information but their willingness in sharing honest reputation information.

In this paper, we propose a trust-oriented mechanism built on a game theoretic basis, to assist buyers to properly report and select sellers in competitive marketplaces. It consists of two major components, trust-oriented seller reporting (TOSR) and trust-oriented seller selection (TOSS). The TOSR component is proposed for buyers to determine their optimal reporting strategy, by 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 this component, buyers not only model the competency of advisers in reporting seller information, but also advisers' willingness to share 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.

The TOSS component is proposed for buyers to discover sellers who maximize their profit by modeling the trustworthiness of sellers and considering the buyers' preferences on product quality (Quality of service, QoS). More specifically, after discovering sufficient reputation information about sellers, a buyer first aggregates its own experience with the sellers and gathers evidence from advisers to determine the trustworthiness of the sellers by taking into account the trustworthiness of the advisers modeled in the TOSR component. Then, the buyer selects a subset of trustworthy sellers as potential business partners and invites them to participate in a trust-aware multi-attribute First-scored Sealed Bid Procurement (FSBP) auction. The winning seller is the one who maximizes the buyer's utility by gaining sufficient trust from the buyer and fulfilling the buyer's QoS preferences.

To evaluate the proposed trust-oriented mechanism, we have conducted three sets of experiments. In the first set of experiments, we validate the 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 surpasses others 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. We also evaluate the efficacy of the TOSS component in different scenarios. In the second set of experiments, the trust modeling based on TOSR is compared with some of the existing trust models in three environments with different levels of competition. For the sake of comparison fairness, we choose four models to compare with, namely TRAVOS [20], BLADE [17], the Personalized Approach [27], and PRep [7], as they are the only approaches in the literature that employ the concept of *advisers* in a similar context and propose a computational model for evaluation of their trustworthiness. The experimental results demonstrate that our proposed trust modeling approach can outperform other approaches, especially in competitive environments. In the third set of experiments, we compare the TOSS component with the original FSBP auction to verify the TOSS component in the three environments with different degrees of competition. We observe that, with the employment of our proposed TOSS model, buyers can obtain higher utility and conduct transactions with more trustworthy sellers, especially in competitive environments. It also confirms that the TOSS component can effectively protect buyers from conducting transactions with untrustworthy sellers, which provides the incentive for sellers to be honest in e-marketplaces regardless of their inventory.

The rest of the paper is organized as follows. Related work is presented in Sect. 2. Section 3 introduces the TOSR component where buyers determine their reporting strategies on the basis of a game theoretic approach and explains the process of modeling advisers' competency and willingness values. Section 4 introduces the TOSS component where buyers model the trustworthiness of sellers, select trustworthy sellers to join a trust-aware multi-attribute FSBP auction, and finally determine the winner of the auction. In Sect. 5, we present simulation settings and experimental results. Finally, we conclude the current work and propose future research in Sect. 6.

2 Related work

In [10], a side payment mechanism to offer honest advisers some extra utility is proposed, by virtue of which it is better for advisers to truthfully report reputation information about sellers. The work also raises the concern that reporting truthfully may cause some cost to advisers but does not study this issue further in competitive e-marketplaces where the cost of losing business opportunities because of truthful reporting cannot be simply ignored.

The trust-based incentive mechanism proposed in [27] also tries to create incentives for advisers to truthfully report seller reputation information by offering honest advisers greater discounts from sellers. The basic idea is that, since an honest adviser is most likely the neighbour of many other buyers, if a particular seller offers a discount to an honest adviser, that adviser will promote the seller by propagating the feedback to his social network (neighbours). Hence, the seller would be able to attain more profit in its future transactions. In order to gain a better discount, advisers prefer to truthfully report seller reputation information in this mechanism.

In general, the side payment and the 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 decide theirs. Furthermore, revealing actual intentions and willingness of agents is not a trivial task and has been neglected in these mechanisms. 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 also been proposed to evaluate the trustworthiness of advisers. Zhang [27] proposed a personalized approach to estimate the trustworthiness of advisers. In this model, advisers share their ratings about some sellers. This model exploits a probabilistic approach and calculates the expected value of advisers' trustworthiness by integrating the public and private reputation components about advisers based on their provided ratings.

FIRE [8] defines an adaptive inaccuracy tolerance threshold based on the selling agent's performance variation to specify the maximal permitted differences between the actual performance and the provided ratings. Trustworthiness of advisers is tuned to be inversely proportional to the differences, i.e., the higher the differences, the lower their trustworthiness.

In TRAVOS [20], 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.

BLADE [17] provides a model for buyers to interpret evaluations of advisers using a Bayesian learning approach. In BLADE, buyers model sellers' properties and advisers' evaluation functions; thus, misleading reports provided by dishonest advisers would be re-interpreted or corrected, instead of being discounted or filtered. Therefore, BLADE can effectively re-interpret the deliberated ratings. A similar approach, the Probabilistic Reputation model (PRep) [7], is another reputation model to evaluate the behaviour of an adviser based on a Bayesian learning approach, which re-interprets the reported information. The main difference of these two models is related to the types of advisers they consider. BLADE considers the evaluation functions (the probability of an adviser reporting the same ratings with a buyer and the probability of reporting different ratings with the seller), and PRep focuses on the bias types (the probability of an adviser reporting *positive* when the actual outcome is *negative* and the probability of reporting *negative* when the actual outcome is *positive*). Both models suffer from the following two shortcomings. Firstly, if advisers do not deliberately provide ratings and dynamically change their behaviour patterns, the two models cannot learn an accurate evaluation function or behaviour probability for them. Secondly, the Bayesian learning process requires a sufficiently large amount of transaction information (reports) to support high learning accuracy. In competitive e-marketplaces, sellers have limited inventory to sell, thus buyers are unable to always have access to such sufficient information.

Noorian et al. [14] introduced a two-layered filtering algorithm that aggregates several parameters in deriving the trustworthiness of advisers. In addition to the similarity degree of advisers' opinions, the Prob-Cog model [15] aggregates their behavioural characteristics (i.e. optimism, pessimism and realism) and evaluates the adequacy of their reputation information in the credibility measure. In this model, every buyer with different behavioural characteristics is able to objectively evaluate the similarity degree of advisers through a multi-criterion rating approach. Also, buyers could adaptively predict the trustworthiness of advisers using different credibility measures well-suited for various kinds of advisers.

PeerTrust [25] is a coherent dynamic trust model for peer-to-peer e-commerce communities. To evaluate the quality of the feedback provider (adviser), it proposed a personalized similarity measure to compute a feedback similarity rate between the evaluating peer and advising peer over a common set of peers with whom they have had previous interactions. Particularly, this model calculates the root-mean-error or standard deviation of the two feedback vectors to compute the feedback similarity. Through this principle, the evaluating peer discounts the previous feedback released by advisers.

Yu and Singh [26] proposed a decentralized reputation management model to locate trustworthy advisers in multi-agent systems. One of the major concerns of this model is to detect malicious advisers who deliberately disseminate false information through a network. The proposed model considers three types of deception: complementary, exaggerative positive and exaggerative negative. It defines an exaggeration coefficient to differentiate between exaggerative and complementary deceptive agents. This model uses the same credibility measure to calculate the trustworthiness of different kinds of advisers by considering how much their ratings deviate from the actual value experienced by a buyer.

These existing trust models, however, do not consider the willingness of advisers in providing seller reputation information because these models were proposed for e-marketplaces with infinite (or very large) inventory. These models assume that advisers consistently behave according to their degree of credibility or other endogenous characteristics. However, in competitive marketplaces, credible advisers might adopt different reporting behaviours despite their dispositions. Our proposed approach allows buyers to model the willingness of advisers so as to dynamically determine the trustworthiness of advisers' reports.

Moreover, in e-marketplaces, buyers need to select sellers to conduct transactions. In the First-scored Sealed Bid Procurement (FSBP) auction [3], sellers place their bids in a sealed envelope and submit them to the auctioneer (buyer). The buyer will then choose the bidder who offers the best price as its business partner. Later, [6] extends this auction model and proposes the multi-attribute FSBP in which the auctioned item is defined by several QoS attributes. In this auction model, the winning seller is the one who maximizes the scoring function of buyers, which is the combination of quality attributes and offered price.

Zhang [28] proposed a centralized service selection mechanism where the central server runs the procurement auction and maintains information that is shared with sellers and buyers. In this auction where the auctioneer is a buyer and bidders are sellers, a buyer announces its intention to purchase a product along with its evaluation criteria to the central server. The buyer then limits the number of participating sellers in the auction by modeling their trustworthiness using its own observations and the feedback provided by its advisers and finally chooses the seller whose product gives the buyer the largest profit based on the buyer's evaluation criteria.

Another approach for an efficient service selection is proposed by [21]. They proposed a generic service selection model, based on decision theory concepts [1], consisting of two parts. First, a truster (i.e. buyer) would realize possible outcomes of interacting with different trustees (sellers) and identify how much the truster prefers each possible outcome. The preference of the truster is quantified by a utility function that defines the value of each interaction outcome with trustees. Second, for each trustee, the truster evaluates the likelihood of the possible outcomes based on available evidence including its personal experience and reputation. Finally, the truster selects a trustee who yields the highest expected utility as the interaction partner.

As can be observed, in the presented service selection methods, buyers would not consider the trustworthiness of sellers in their winner determination process. Thus, in this paper, we further extend the generic FSBP auction model to *trust-aware* multi-attribute FSBP, which integrates the trustworthiness of sellers as an influential element in the winner determination strategy. Determining the winning seller would be based on the optimized combination of the seller's trustworthiness, quality attributes and offered price that yields the highest performance/profit for buyers. We also found that the proposed trust-aware multi-attribute FSBP approach mostly fits with the characteristics of the competitive electronic marketplaces where good sellers are scarce and have limited inventory. This seller selection approach helps buyers to critically evaluate the products based on their subjective preferences and select the sellers who best meet their requirements and have a high level of trustworthiness.

3 TOSR: trust-oriented seller reporting

In this section, we present the trust-oriented seller reporting component of our trust-oriented 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. For the purpose of clarity and convenience, we summarize the notations used in this paper in Table 1.

3.1 Game theoretic basis

As mentioned in Sect. 1, 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 its 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 its 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

Table 1 The explanation of notations

Symbols	Explanations
a_i	An adviser
A	Set of advisers
s_j	A seller
S	Set of sellers
b	A buyer
$V_p(a_i)$	Importance degree of adviser a_i
$T_r(a_i)$	Trustworthiness of adviser a_i
$T_r(s_j)$	Trustworthiness of seller s_j
$C_p(a_i)$	Competency of adviser a_i
$W_i(a_i)$	Willingness of adviser a_i
R_{ij}	Rating vector provided by adviser a_i for seller s_j
$\|R_{ij}\|$	Length of vector R_{ij}
R_{bj}	Rating vector of b for s_j
$P_r(R_{ij})$	Probability of a positive outcome based on R_{ij}
$C_r(R_{ij})$	Reliability degree of R_{ij}
$U_n(a_i)$	Uncertainty degree of a_i
$D_h(a_i)$	Dishonesty level of a_i
$O_e(s_j)$	Expected outcome of s_j
$O_a(s_j)$	Actual outcome of s_j
$H_b(a_i)$	Honesty degree of b in revealing information to a_i
$r(a_i)$	Opinion of a_i
$T_b(s_j)$	Private reputation of s_j based on R_{bj}
$T_A(s_j)$	Public reputation of s_j based on R_{ij} where $a_i \in A$
ϖ	The level of confidence in reputation components
θ	Cost of improving the quality of the product
$U(b)$	Expected utility of b
$Q(s_j)$	Expected value of the product provided by s_j
$M^*(s_j)$	Price charged by s_j for the product
$\Pi(b)$	Scoring function of b in choosing a seller
Ω	Vector of b's preference, $\omega_k \in \Omega$
$W_b(s_j)$	Vector of weights of b for product attributes from s_j
$V_k^*(s_j)$	Attribute k's value of the product provided by s_j

will not be able to gain truthful information about sellers and quickly discover 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 Iterated Prisoner's Dilemma (IPD) game. In the IPD, the game is repeated indefinitely. In each round of the game, where buyers decide to purchase certain products, they evaluate the expected

Table 2 Prisoner's dilemma payoff matrix

	Cooperate		**Defect**	
	Agent 1	**Agent 2**	*Agent 1*	**Agent 2**
Cooperate	R	$\mathbf{R}$	K	$\mathbf{T}$
Defect	T	$\mathbf{K}$	P	$\mathbf{P}$

payoff that they can obtain for adopting different reporting strategies and select the one that yields the largest payoff.

Theoretically speaking, in the IPD game, each strategic buyer has some amount of private information about sellers, but not enough to effectively choose a good seller with whom the buyers will conduct transactions. There are two strategies for the strategic buyers in each single shot PD game, i.e., *cooperate* and *defect*, and the payoff matrix is shown in Table 2. If two strategic buyers cooperate by providing each other truthful seller reputation information, each buyer will gain a certain unit of reward R (or $\mathbf{R}$)[1], as both of the two buyers can make a better decision in choosing sellers. If one buyer cooperates and the other defects, then the cooperator receives K (or $\mathbf{K}$) and the defector gains T (or $\mathbf{T}$). Since the cooperator receives untruthful information, which is provided by the defector, he would make a worse decision, which leads to $K < R$. Meanwhile the defector can make an even better decision based on the truthful information shared by the cooperator and the decreased competition for the limited good sellers through misleading the cooperator, which leads to $R < T$ and $\mathbf{R} < \mathbf{T}$. In the case where both of the two buyers defect by providing untruthful information, both of them will be punished by obtaining a lower payoff P (or $\mathbf{P}$) satisfying $P < R$ (or $\mathbf{P} < \mathbf{R}$) due to the misleading effect caused by untruthful information. Given that one buyer defects, the other buyer will be misled for certain and he will prefer to defect rather than cooperate, because its truthful information provided will increase the competition for the limited good sellers, which makes his payoff even worse, i.e. $K < P$ and $\mathbf{K} < \mathbf{P}$. Therefore, we can conclude that $K < P < R < T$ (and $\mathbf{K} < \mathbf{P} < \mathbf{R} < \mathbf{T}$) in competitive marketplaces.

Similar to the IPD 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 few rounds 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 in the IPD game adopted in competitive marketplaces, i.e., exposing truthful reputation information, inspired by the idea presented in [18], as follows:

$$U_c = V_p * \left(R + \min(\bar{\gamma_1}, \bar{\gamma_2}) * \frac{R}{1 - \min(\bar{\gamma_1}, \bar{\gamma_2})} \right) \tag{1}$$

where V_p represents the *importance degree* of the interaction partner. Since V_p can positively foster cooperation between buyers (i.e. a buyer would prefer to perform cooperation with a more important buyer, and the formalization of V_p is available in the following subsection), we consider this effect by multiplying V_p with expected utility.

$\bar{\gamma_1} = 1 - \gamma_1$ and $\bar{\gamma_2} = 1 - \gamma_2$ 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. This

[1] R is not necessarily equal to $\mathbf{R}$ but in the experiments of this paper we assume that they are the same. The model can also be applied to the case where the value of R is different for each buyer.

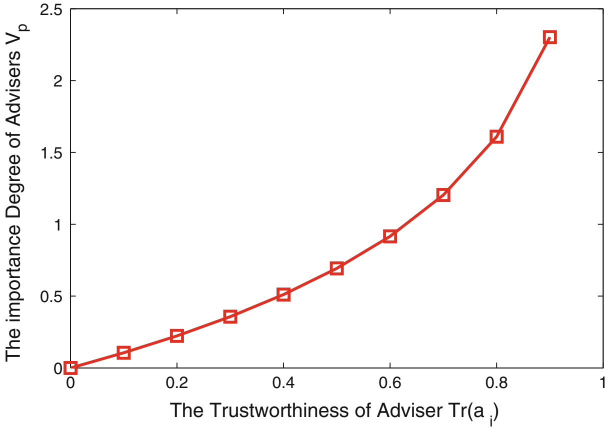

Fig. 1 The importance degree of partners based on their trustworthiness

idea has been motivated by the Bellman Equation [22] capturing the fact that an agent's reward does not only depend on the immediate reward but also on its future discounted rewards.

γ_1 and γ_2 indicate the age of the two buyers respectively, i.e., the duration that the two buyers have been in the e-marketplace, which is maintained by the central server. Each buyer has a certain purchase mission, which will be started right after the buyer joins the marketplace. As the age 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 $\bar{\gamma_1} = 1 - \gamma_1$ or $\bar{\gamma_2} = 1 - \gamma_2$ is very small, the promise of future payoffs is not sufficient to encourage the buyers' cooperative behaviour.

Similarly, the expected payoff of the buyers who always take the defect strategy (i.e. reporting untruthful seller reputation information) can be computed as follows:

$$U_d = \frac{1}{V_p} * \left(T + \min(\bar{\gamma_1}, \bar{\gamma_2}) * \frac{P}{1 - \min(\bar{\gamma_1}, \bar{\gamma_2})} \right) \tag{2}$$

Equation (2) implies that, in our proposed approach, a buyer prefers to defect towards an unimportant buyer (adviser). It is also 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. Based on the Grim strategy, a buyer will 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 Eqs. (1) and (2)), we further define a distribution of $V_p(Tr_{(a_i)}) = -\log(1 - Tr_{(a_i)})$ [18] where $Tr_{(a_i)}$ represents the trustworthiness of the partner (adviser a_i), which will be formalized in the next section. We specifically employ this distribution model as it provides a low-value stakes when $Tr_{(a_i)}$ is in [0, 0.5] and it provides a high-value stakes when $Tr_{(a_i)}$ falls within [0.5, 1].

Figure 1 illustrates this distribution more clearly. Using this distribution, buyers appreciate those partners with high trustworthiness by adopting cooperative attitudes in their interactions.

3.2 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 (Eqs. (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. Therefore, a trustworthy adviser should be a competent adviser who is also willing to report his truthful information. Based on this intuition, the trustworthiness of an adviser a_i, where $a_i \in A = \{a_1, a_2, \ldots, a_n\}$, is then calculated as follows:

$$T_r(a_i) = C_o(a_i) * W_i(a_i) \tag{3}$$

Here, $C_o(a_i) \in [0, 1]$ is the competency of adviser a_i in reporting accurate seller information, and $W_i(a_i) \in [0, 1]$ is the willingness of a_i in truthfully reporting seller information. We will describe the modeling of these two factors in the next two subsections.

3.2.1 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_{ij} for each seller, for example s_j. It contains a tuple $\langle r, s \rangle$, 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_{ij}, buyer b calculates the expected value of the probability of a positive outcome ($P_r(R_{ij})$) for seller s_j based on a beta distribution [9] as follows:

$$P_r(R_{ij}) = \frac{r+1}{r+s+2} \tag{4}$$

Clearly, $0 < P_r(R_{ij}) < 1$ and as it approaches 0 or 1, it indicates *unanimity* in the body of evidence [24]. That is, particularly large values of s or r provide better intuition about an overall tendency and quality of sellers. In contrast, $P_r(R_{ij}) = 0.5$ (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 (1) and (3) in [24], the *reliability degree* of each R_{ij} can be defined as follows:

$$C_r(R_{ij}) = \frac{1}{2}\int_0^1 \left| \frac{x^r(1-x)^s}{\int_0^1 x^r(1-x)^s\,dx} - 1 \right| dx \tag{5}$$

Theoretical analysis [24] demonstrates that, for a fixed ratio of positive and negative observations, the reliability increases as the number of observations increases. On the contrary, given a fixed number of observations, as the extent of conflict increases, the reliability of the provided observations decreases accordingly. That is, reliability is at a minimum when $P_r(R_{ij}) = 0.5$. 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_{ij} 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 products 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 $P_r(R_{bj})$ and $C_r(R_{bj})$ based on her personal experience, R_{bj}, with a set of sellers S with whom the advisers also have experience.[2] Through the comparison of advisers' metrics with the buyer's experience, 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:

$$D_h(a_i) = \frac{\sum_{j=1}^{|S|} \mid P_r(R_{bj}) - P_r(R_{ij}) \mid}{|S|} \tag{6}$$

It may also happen that an honest adviser lacks experience with sellers. Thus, despite her inherent honesty, its reliability degree is low and it should not be highly trusted. To address this, we introduce an uncertainty function $U_n(a_i)$ to capture the intuition of information imbalance between b and a_i as follows:

$$U_n(a_i) = \frac{\sum_{j=1}^{|S|} \mid C_r(R_{bj}) - C_r(R_{ij}) \mid}{|S|} \tag{7}$$

Given the level of dishonesty of adviser a_i, the honesty of the adviser could be calculated as $1 - D_h(a_i)$. Similarly, given the uncertainty of adviser a_i, the certainty of the adviser would be $1 - U_n(a_i)$. Thus, a competent adviser should achieve higher honesty and certainty simultaneously. The *competency degree* of adviser a_i is then calculated by reducing her honesty based on her certainty degree as follows:

$$C_o(a_i) = (1 - D_h(a_i)) \times (1 - U_n(a_i)) \tag{8}$$

3.2.2 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 opinion about the requested seller, $r(a_i)$, which is the interaction outcome of adviser a_i with a particular seller that is shared with b, and the mean value of the ratings provided by all advisers and the buyer b; (2) the degree of honesty, $H_b(a_i)$, of the buyer b in revealing the reputation information to

[2] Here, we choose a set of sellers $S \subset \{s_1, \ldots, s_m\}$ with whom buyer b has sufficient experience, to make sure that the buyer has sufficient knowledge to judge the advisers.

adviser a_i, which is the ratio of the number of truthful ratings to the total number of ratings provided by a_i. More formally, the trustworthiness of an adviser is calculated as follows:

$$W_i(a_i) = H_b(a_i) * e^{-\mathrm{Dev}^t_{(a_i)}} \tag{9}$$

$$\mathrm{Dev}^t_{(a_i)} = \int_0^{\mathrm{Dev}^{t-1}_{(a_i)} + |r_{(a_i)} - \mu|} e^x \,\mathrm{d}x, \quad \mathrm{Dev}^0_{a_i} = 0 \tag{10}$$

where μ indicates the mean value of the provided ratings by all advisers and the buyer b. The $\mathrm{Dev}^{t-1}_{(a_i)}$ indicates the difference accumulated during the previous transactions until a period $t-1$, and the $\mathrm{Dev}^t_{(a_i)}$ is the one considering the transaction period t.

Suppose that the buyer b wants to calculate the willingness of the adviser a_i after obtaining the actual interaction outcome with the recommended seller. To calculate $\mathrm{Dev}^t_{(a_i)}$, the buyer b first calculates the mean value, μ, of the ratings provided by all the advisers. Then, b continuously accumulates the differences of a_i's rating, $r(a_i)$, with computed μ (considering the previous deviation of a_i's ratings captured through $\mathrm{Dev}^{t-1}_{(a_i)}$). Note that we specifically exploit the e^x function since it exponentially grows as the difference of the adviser's rating with the mean value increases. To calculate $H_b(a_i)$, b calculates the ratio of honest ratings to total ratings shared with a_i. The key intuition is that a_i would be more likely to share honest ratings with the buyer b if the buyer b retaliates accordingly and has provided honest information to a_i when requested. Finally, we multiply these two factors to calculate the willingness of a_i as $W_i(a_i)$.

Note that the strategic buyer initially assumes that advisers provide ratings according to their endogenous behavioural characteristics evaluated as the competency in the previous subsection, and thus adjusts $W_i(a_i) = 1$ for all advisers. However, as time progresses, the strategic buyer learns advisers' attitudes and updates their willingness accordingly.

The buyer also takes into account the differences of the behavioural dispositions of advisers and would not degrade their willingness unless their ratings significantly diverge from μ in certain circumstances. The Eqs. (11) and (12) demonstrate the conditions where the willingness of an adviser should be updated. After each business interaction, a buyer examines the two conditions. If either of these conditions has been satisfied, the buyer will continuously update the willingness of the adviser using Eq. (9).

More formally, given the expected interaction outcome, $O_e(s_j)$, and the actual outcome, $O_a(s_j)$, of the buyer with a seller s_j, the willingness of adviser a_i would be updated under the following conditions:

$$O_a(s_j) > (1+\epsilon) \times O_e(s_j) : \begin{cases} r(a_i) < \mu - \sigma \\ r(a_i) < \mu \;\; \wedge \;\; \frac{\sigma}{\mu} > \eta \end{cases} \tag{11}$$

$$O_a(s_j) < (1-\epsilon) \times O_e(s_j) : \begin{cases} r(a_i) > \mu - \sigma \;\; \wedge \;\; \frac{\sigma}{\mu} < \eta \\ r(a_i) > \mu \;\; \wedge \;\; \frac{\sigma}{\mu} > \eta \end{cases} \tag{12}$$

To explain, in the case where $O_a(s_j)$ surpasses $O_e(s_j)$ by a percentage ϵ, which is a threshold to trigger the updating, a strategic buyer updates those advisers whose ratings are significantly below μ. In Eq. (11), η represents an acceptable level of dispersion in advisers' feedback. We calculate the ratio of σ (the standard deviation of the provided ratings) and μ as the coefficient of variation, which articulates the quality of dispersion of the provided ratings. As σ/μ 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 [26]. Through proper adjustment of η, 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. $O_a(s_j) < (1-\epsilon) \times O_e(s_j)$, a strategic buyer adjusts the willingness of advisers whose ratings are around μ. In Eq. (12), 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 μ. Note that through introducing ϵ, we give strategic buyers the flexibility to adaptively determine the acceptable margin of differences between $O_a(s_j)$ and $O_e(s_j)$ pertaining to their own behavioural patterns and environmental conditions.

4 TOSS: trust-oriented seller selection

In competitive e-marketplaces where high quality products are limited, buying agents compete to increase their revenue by transacting with qualified sellers. They evaluate the proficiency of selling agents and select ones who maximize their profits. The key intuition in the determination of the expected utility of a buyer when interacting with a certain seller would be based upon the trustworthiness of the sellers and their quality in fulfilling the buyer's demands.

To formalize the TOSS component of selecting the most appropriate sellers, we consider the scenario in competitive e-marketplaces where a particular buyer intends to purchase a certain product. First, it models the trustworthiness of a variety of sellers who supply that product by integrating its own experience and advisers' information about seller reputation, taking into account the advisers' trustworthiness. Next, it initiates negotiation with highly trustworthy sellers in a procurement auction and selects the winning seller who satisfies its expectations to the highest degree. The next subsections are devoted to describing the detailed steps of the TOSS component.

4.1 Modeling the trustworthiness of sellers

Buyers model the trustworthiness of sellers by combining their personal experience with sellers and the reputation information about the sellers provided by advisers. To formalize our approach, we define two information components. One component evaluates the sellers based only on the buyers' personal experience with the sellers. The result is referred to as the private reputation of the sellers. Another component evaluates the sellers based only on the reputation information of sellers shared by the advisers. This component also takes into account the trustworthiness of the advisers when integrating the advisers' information. The result of this component is referred to as the public reputation of the sellers. Finally, we combine the results of these two components to derive the trustworthiness of the sellers.

More specifically, suppose that a buyer b has a rating vector R_{bj}, which contains all the rating reports provided by b along with their corresponding time of interactions with the seller s_j. The private reputation of s_j based on b's direct experience can be estimated as follows:

$$T_b(s_j) = \frac{\sum_{r_k \in R_{bj}} r_k \times RF(r_k)}{\sum_{r_k \in R_{bj}} RF(r_k)} \tag{13}$$

where

$$RF(r_k) = e^{\frac{(t_p - t_c)}{\lambda}} \tag{14}$$

represents the time weighting factor of rating r_k [2]. In this trustworthiness calculation formula, the notion of time is captured by a *Recency Factor* $RF(r_k)$, which measures the recency of transaction results stored by the buyer b. That is, as the difference between the current time (t_c) and the time of the previous interaction (t_p) increases, the significance of the former transaction result deteriorates substantially. The λ parameter, which resides in the range [0, 1], defines the rate of deterioration of the reputation values and enables participants to determine the importance degree of the previous ratings adaptively. For instance, in a dynamic environment where sellers frequently alter their behaviours, setting λ to a smaller value enables buyers to rely more on their own *very recent* experience. On the other hand, as the λ value increases, the deterioration rate becomes smaller, resulting in the augmentation of the importance of previous ratings. We conjecture that the recency factor could serve as a defensive mechanism against the changeability of sellers' behaviour.

The buyer b also considers ratings provided by their advisers to model the public reputation of seller s_j. Suppose that advisers $A : \{a_1, a_2, \ldots, a_m\}$ have provided ratings for s_j. We formulate the public reputation of sellers by calculating the weighted average of all advisers' ratings, where the weight of a rating incorporates the trustworthiness of the adviser in providing the rating as well as the recency of the rating. The public reputation value of s_j based on the advisers' reputation information can be estimated as follows:

$$T_A(s_j) = \frac{\sum_{i=1}^{m} r(a_i) \times T_r(a_i) \times RF(r(a_i))}{\sum_{i=1}^{m} T_r(a_i) \times RF(r(a_i))} \tag{15}$$

According to Eq. (15), the expected trust value of s_j based on the advisers' experience depends mainly on an adviser's degree of trustworthiness $T_r(a_i)$ (see Eq. (3)) in their provided ratings and the age of their provided ratings.

Once we have calculated both the private and public reputation values of s_j based on the available information components, it is required to integrate the intermediate results and generate a final value for the expected trustworthiness of s_j. Nevertheless, in order to confidently predict the trustworthiness of sellers, it is necessary to proportionately weight the components according to their level of importance. For instance, in case a buyer lacks personal experience, the evidential reports exposed by advisers seem to be more important compared with the situation when the buyer has abundant personal evidence. In other words, the adequate amount of personal experience prevails over other available reputation information released by even the most trustworthy advisers. Thus, the trustworthiness of a seller is estimated by combining the weighted private and public reputation as follows:

$$T_r(s_j) = \varpi \times T_b(s_j) + (1 - \varpi) \times T_A(s_j) \tag{16}$$

A possible solution to measuring ϖ is to calculate the minimum number of personal rating reports that should be maintained by a buyer, which makes it confident about the private reputation value it has for a seller s_j. To operationalize this goal, the Chernoff Bound theorem [12] is exploited to compute the minimum number of ratings, $\tau_{\min}$, necessary to achieve the desired level of confidence ϖ within a specific margin of error ϵ.

$$\tau_{\min} = -\frac{1}{2\epsilon^2} ln \frac{1-\gamma}{2} \tag{17}$$

Motivated by [27], the weight function of each individual information component can be defined as

$$\varpi = \begin{cases} \frac{|R_{bj}|}{\tau_{\min}} & |R_{bj}| < \tau_{\min} \\ 1 & \text{otherwise} \end{cases} \tag{18}$$

According to Eqs. (16) and (18), the influence of advisers' observations is curtailed in light of increasing a buyer's direct experience resulting in the increment of their confidence degree within the predefined error bound. Note that the confidence rate can be chosen indigenously by buyers pertaining to their behavioural characteristics and information availability.

Finally, the buyer would classify the sellers whose trustworthiness $T_r(s_j)$ is above the pre-defined reputation threshold as *potential* sellers and would filter out the rest.

4.2 Trust-aware FSBP auction

In this section, we first present the First-score Sealed-Bid Procurement (FSBP) auction model as our seller selection approach. The idea has been initially presented in some valuable previous works [3,5,6]. However, we argue that the traditional FSBP auction model cannot be simply adopted as our seller selection methodology as it does not incorporate the trustworthiness of sellers in buyers' decision making process. Thus, we extend this auction model by adding a seller trustworthiness calculation component, as presented in Sect. 4.1, and propose a trust-aware FSBP auction model.[3]

To formalize, we suppose that in the competitive e-marketplace the transactions between buyers and sellers happen in the form of FSBP auctions. In the FSBP process, a buyer announces the list of negotiable attributes and its preferences concerning the requested product's properties, and invites potential sellers to submit their multidimensional bids on the predefined attributes. Next, the buyer assesses the submitted bids, ranks them according to its preferences on the attributes and designates a contract to the seller who maximizes its utility.

Similar to [6], in the proposed trust-aware FSBP auction process, each seller has private information about the cost of improving the quality of the product it provides. As the cost parameter θ increases, the cost of the seller for supplying a higher quality of product increases correspondingly. Buyers do not have any information about the actual cost parameter of each seller, instead, they are only aware of the uniform distribution function of this parameter over $[\underline{\theta}, \bar{\theta}]$ where $(0 < \underline{\theta} < \bar{\theta} < \infty)$. In addition, we consider the attributes as utility independent. In other words, the utility of one attribute does not depend on the utility of any other attributes [23].

The buyer initializes the trust-aware FSBP auction by announcing its requirement for the particular product in the form of a *scoring function*. The scoring function is designed to be similar to the utility function as it reflects the buyer's preferences over different criteria of the product. Using this function, the buyer associates a score with each proposed offer and then selects the subset of them having the maximum scores as its candidate sellers. Note that this function is used by the buyers as a tool for choosing a set of optimum bidders and also for providing bidders with the benchmark to derive their optimal bids considering the buyer's preferences. After that, the sellers who are allowed to participate in the auction submit their sealed bids that include the detailed description of their products considering the buyer's scoring function. Finally, the buyer selects the winner of the auction, who gives the buyer

[3] We notice that a trust-aware FSBP auction model is not an application but an extension built on the previous work.

the largest profit based on the buyer's utility function. It is noteworthy to mention that, in the proposed seller discovery methodology, malicious sellers would not find an opportunity to participate and submit compelling bids since they have been already filtered.

In our proposed mechanism, the adopted utility function of buyers is not simply an additive weighting utility function, which combines different weighted attributes into a decision rule, as exploited in [3,4,6,19]. Instead, we propose a specific utility function for buyers that incorporates the internal characteristics of sellers such as their trustworthiness. The rationale underlying the design of such a utility function is that the buyer seeks to award a contract to the seller s_j who offers the best combination of performance, price and reliability and not necessarily to the seller who offers the lowest price. Based on these principles, the buyer b's utility $U(b)$ is formalized as follows:

$$U(b) = Q(s_j) - M^*(s_j) \tag{19}$$

where

$$Q(s_j) = T_r(s_j) \times \sum_{k=1}^{m} \omega_k \times \sqrt{V_k^*(s_j)} \tag{20}$$

As shown in Eqs. (19) and (20), the utility of a buyer b depends not only on the cost a seller s_j charges b for the particular product ($M^*(s_j)$), but it also relates to the quality of sellers ($Q(s_j)$). If we consider m arbitrary attributes for the product provided by seller s_j, $Q(s_j)$ can be computed based on the quality value of each criterion k that s_j claims to fulfill, $V_k^*(s_j)$, given b's preferences ($\omega_k \in \Omega$ where $k \in \{1, \ldots, m\}$). The domain of $V_k^*(s_j)$ would be any nonnegative value and we consider ω_k to have a discrete value within [1, 10]. The utility function gaining from a quality value $V_k(s_j)$ is concave, i.e. the first order derivative is positive and the second order derivative is negative. To model the concaveness of the utility function, we apply the square root function, which is well-studied in the literature [6]. Moreover, unlike other e-auction environments [3,6,19], which assume that sellers will deliver the exact service as negotiated, in this model we capture the uncertainty characteristic of such an environment and discount the claims of sellers based on their trustworthiness $T_r(s_j)$ in delivering their previous commitments.

Nevertheless, the weight vector Ω is private and a buyer can reveal any weight W_k which may be equal or different from the actual weight vector $\omega_k \in \omega = \{\omega_1, \ldots, \omega_m\}$ that the buyer considers for its negotiating attributes.

Motivated by the formulation of the utility function, we can compute the scoring function of the buyer b, $\Pi(b)$ as follows:

$$\Pi(b) = -M^*(s_j) + T_r(s_j) * \sum_{k=1}^{m} W_k \times \sqrt{V_k^*(s_j)} \tag{21}$$

where $W_k \in W(s_j) = \{W_1, \ldots, W_m\}$ are the weights that b reveals with respect to attribute k of seller s_j.

4.3 Analyzing buyer and seller behaviour

Arbitrary alteration of the weights provides buyers with the ability to explicitly demonstrate their leaning towards different attributes without revealing their actual preferences. Buyers subjectively calculate W mainly based on the importance of each particular attribute and the trustworthiness of the sellers. As such, W for sellers with different trustworthiness values would be initialized differently. That is, in the competitive e-marketplace with a certain number of sellers having a uniform cost distribution, buyers differentiate highly trustworthy sellers by announcing W as $W \simeq \omega$ so as to give them an opportunity to bid higher quality of products with trivial price augmentation. On the other hand, buyers conceal their actual preferences for sellers with low trustworthiness by providing W as $W < \omega$. This valuation prevents them from offering products with high quality attributes in order to be able to compete with highly trustworthy sellers. Evidently, the adaptive valuation of W for various selling agents reduces the chance of sellers with low trustworthiness winning the competition and being selected as the winning business partners.

Thus, according to Theorem 1 in [5,6], for n sellers, if we consider the buyer's actual weights ω and given the distribution of the sellers' cost parameter and seller s_j trustworthiness value $T_r(s_j)$, we formulate the optimal value for W_k for a particular seller s_j in the proposed trust-aware FSBP auction protocol as follows:

$$W_k^* = T_r(s_j) \times \omega_k \times \frac{\int_{\underline{\theta}}^{\bar{\theta}} \frac{(\bar{\theta}-t)^\alpha}{t} dt}{\left(\int_{\underline{\theta}}^{\bar{\theta}} \frac{(\bar{\theta}-t)^\alpha}{t} dt + \int_{\underline{\theta}}^{\bar{\theta}} \int_t^{\bar{\theta}} \frac{(\bar{\theta}-z)^\alpha}{z^2} dz dt \right)} \tag{22}$$

where $\alpha = n - 1$ and n is the number of bidders in the auction. Besides the influence of $T_r(s_j)$, empirical studies demonstrate that if the number of sellers increases, the valuation of W in the scoring function would be closer to ω of the utility function [6]. Also, we notice that if the ratio of distribution of the sellers' cost parameter $\bar{\theta}/\underline{\theta}$ is low, i.e., the relation between $\bar{\theta}$ and $\underline{\theta}$ approaches 1, the sellers are homogenous, which implies intense competition between sellers. In such a situation, buyers do not need to alter their weight parameters and can freely reflect their true preferences in their proposed scoring function by adjusting $W = \Omega$. On the other hand, in the case of dealing with heterogeneous sellers (i.e. $\bar{\theta}/\underline{\theta} >> 1$), buyers are motivated to manipulate their real weights and true preferences as strong sellers can take advantage of this situation and increase their profits [5,6].

Unlike the traditional single-attribute procurement auction where sellers decide only about the bidding price, in the multi-attribute FSBP auction, sellers have to propose their bids as a combination of multiple quality attributes and the price parameters, considering their own cost parameters and the buyer's scoring function.

Based on Lemma 2 in [3,5,6], in the proposed trust-aware FSBP auction model, if the seller s_j is aware of the number of competitors n and their cost parameters uniformly distributed in $[\underline{\theta}, \bar{\theta}]$, the dominant bidding strategy for s_j based on its cost parameter θ can be calculated as:[4]

$$V_k^*(s_j) = \left(\frac{W_k(s_j)}{2\theta} \right)^2 \tag{23}$$

where $k \in [1, \ldots, m]$ and

$$M^*(s_j) = \sum_{k=1}^{m} \frac{W_k^2}{4} \times \left(\frac{1}{\theta} + \frac{1}{(\bar{\theta} - \theta)^{n-1}} \cdot \int_{\theta}^{\bar{\theta}} \frac{(\bar{\theta} - t)^{n-1}}{t^2} \right) \tag{24}$$

As observed in Eqs. (23) and (24), the seller s_j decides the value for different attributes on the basis of the buyer's scoring function and its own cost parameter. So, if a large number of sellers is competing in the auction, the dominant strategy for s_j is to decrease its price bid. This formulation also complies with the notion of supply and demand in competitive

[4] In [6] each quality attribute i is characterized with a particular coefficient, which is identical for all sellers. In our model, we consider all coefficients as 1.

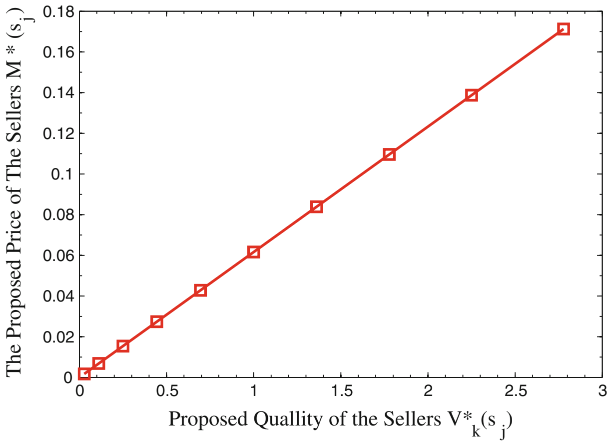

Fig. 2 The relationship of the quality and price functions when W changes from $\{1, \ldots, 10\}$ with $n = 21$ and $\theta \in [2, 4]$

marketplaces where the number of high-quality products are scarce. In such environments, since the supply is limited and demand high, suppliers would increase the bidding price in order to gain more profit.

We notice that, through adaptive valuation of W and the sellers' bidding strategy, which heavily relies on their trustworthiness, we implicitly define two levels of competition among sellers. The first level is dedicated to those with high levels of trustworthiness who can bid products based on the buyers' real demands. Buyers would announce their actual preferences over different attributes of the product only to highly trustworthy sellers, giving them an opportunity to bid based on their actual requirements. The second level of competition happens among sellers with a rather low trustworthiness value. Since buyers conceal their actual preferences from less trustworthy sellers, they are unable to bid based on buyers' real demands. Evidently, such sellers are inherently doomed to lose in the competition as they could not effectively keep up with the bids of highly trustworthy sellers.

To examine the advantage of trustworthy sellers in accessing the actual preferences of buyers, we have plotted the relationship between the quality and the price function in Fig. 2. We observe that, as W increases so that $W \rightarrow \Omega$, the quality of the proposed product increases considerably more than the bidding price. In other words, since sellers strategically determine their bidding strategies based on the announced preferences of buyers over different attributes, knowing their actual preferences provides trustworthy sellers with the ability to offer higher QoS with not much higher prices, which increases their chance of being selected as a winning bidder.

We can conclude that the proposed seller selection methodology can provide incentives for sellers to act honestly in a competitive e-marketplace in order to increase their revenue.

5 Experimentation and results

We have conducted three sets of experiments and the results are presented in the following three subsections.

In the first set of experiments, the validation of the proposed mechanism is presented. We evaluate the efficacy of the TOSR and TOSS components of our proposed trust-oriented mechanism and examine how different types of buyers deal with different sellers in a competitive resource-limited electronic marketplace.

In the second set of experiments, we compare the proposed trust modeling approach with four existing trust models, namely TRAVOS [20], BLADE [17], the Personalized Approach [27], and PRep [7], in three types of environments with different levels of competition.

In the third series of experiments, we compare the proposed TOSS model with the traditional multi-attribute FSBP auction model in three types of environments so as to demonstrate the performance of our proposed seller selection mechanism in different environmental circumstances.

5.1 Experimental setting

The e-marketplace environment used for experiments is populated with self-interested buyers and sellers, and is operated for 30 days. In this e-marketplace, there are 100 buyers in total, and they have a set of goals of making a purchase of a particular product on every day. Sellers have limited inventory and supply their products with different QoS.

We assume that there are 100 sellers, which supply the same kind of product with different QoS on every day. Therefore, the total number of participating sellers in our system is 100*30 in the 30 days. Among the sellers on each day, half of them are honest and their QoS value of each attribute (i.e. $V_k^*(s_j)$ in Eq. (20)) varies in the range [0.6, 0.95], and the other half are dishonest with their QoS within [0.1, 0.4]. In addition, 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 significantly from their reported values by a number chosen from the normal distribution $N(0.65, 0.02)$.

Moreover, sellers have limited inventory, where we consider three environments: a competitive environment, a semi-competitive environment, and a non-competitive environment, where the inventory number each seller has in these environments is 1, 100/2, and 100 respectively. If each seller has only one item of inventory, we can see that the number of high quality products is much smaller than the number of buyers, which makes it a competitive environment. When the inventory increases to 50, the most trustworthy sellers can serve half of the buyers but still cannot satisfy all buyers, which is the reason we refer to this case as a semi-competitive environment. Finally, the non-competitive environment is the case where the inventory of each seller is equal to the number of the buyers (i.e. 100).

As such, we characterise different environments based on their supply/demand ratio. In a competitive environment, sellers have limited inventory (each seller has only one product). So, in an environment with the same number of buyers and sellers, the supply of good products is lower than their demand as the QoS of some sellers cannot satisfy the demand of buyers. For a non-competitive environment, sellers have unlimited inventory. Each seller provides a large number of products sufficient for all the buyers. Thus, in a non-competitive environment, the demand for good products can be fully satisfied by the supply and there is no competition for the good products. In a semi-competitive marketplace, good sellers have an average amount of inventory sufficient for half of the buyers thus the demand for high quality products is in semi-competition.

The other characteristic that we envision for different environments is that in the competitive environment, *half* of the buyers would perform (i.e., provide seller reputation information) according to their behavioural dispositions, and the other half would behave otherwise. For example, in a competitive market, an *inherently-honest* buyer may intentionally provide *false* feedback to others about the QoS of a particular seller with which it is interested in dealing in the future. Likewise, in the semi-competitive environment, 3/4 of buyers would behave based on their credibility, and the other 1/4 behave despite it. Finally, in the non-competitive environment, *all* buyers would perform based on their internal characteristics. This intuition is naturally supported by the premise that exists in the social sciences [13] stating that people might behave in spite of their actual dispositions in certain situations. That is, honest people may carry out dishonest acts consciously and deliberately to maximize their profits.

In the simulations, we set some parameters for the latter experiments. We randomly select the value of γ_1 and γ_2 used in Sect. 3 from the normal distribution $N(0.05, 0.01)$ for different buyers. We also set the threshold η in Eqs. (11) and (12) to be 0.7 and ϵ used in Eq. (17) 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 mechanism is beneficial.

5.2 Validating the proposed mechanism

The validation experiments contain the following four parts. The first two parts are dedicated to validate the TOSR component of our system. More specifically, we investigate the benefit of being trust-strategic buyers as well as the advantage of modeling advisers' willingness in the competitive marketplace. In the third part, we evaluate the TOSS component. Finally, the fourth part shows the effectiveness of the proposed mechanism in coping with sellers' dynamic behaviour.

5.2.1 The benefit of being trust-strategic buyers

In the first series of experiments, we articulate that adopting honest attitudes would not always lead to an optimum outcome, especially 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 evaluate the profit of different types of buyers occupying different percentages of the e-marketplace. We consider three types of buyers: (1): *ALLC*: the competent buyer with a cooperative attitude who always provides truthful information about seller reputation; (2) *ALLD*: the competent buyer with a defective attitude who always provides untruthful information about seller reputation;[5] (3) the *trust-strategic* buyer who strategically decides the quality of reported seller reputation information based on our TOSR mechanism. In this series of experiments we examine the profit of each group of buyers when they occupy different percentages of the population in the competitive marketplace.

In these experiments, we assume that sellers do not change their behaviours when transacting with different buyers in this e-marketplace. Thus, the deterioration rate λ is set to ∞ in this case. In later experiments, we will evaluate the effect of sellers' changing behaviours.

Figure 3 demonstrates the conditions where the majority of buyers are ALLC in a marketplace. We notice that trust-strategic buyers surpass others and obtain the largest profit as they are able to analyse the behavioural patterns of their advisers in order to cooperate with honest advisers by sharing truthful seller information and retaliate against dishonest ones by sharing untruthful seller information appropriately. ALLD buyers can also gain a higher profit than ALLC buyers as they receive accurate seller reputation information from others, specifically from ALLC buyers, but send distorted information in return. ALLC buyers perform the worst.

[5] The buyers adopting the ALLC and ALLD strategies only model the competency of advisers, that is $T_r(a_i) = C_o(a_i)$.

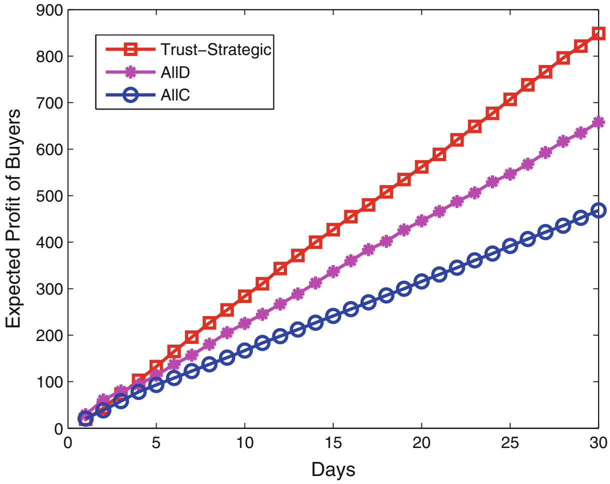

Fig. 3 The profit of different types of buyers where ALLC buyers occupy 70 % of the system

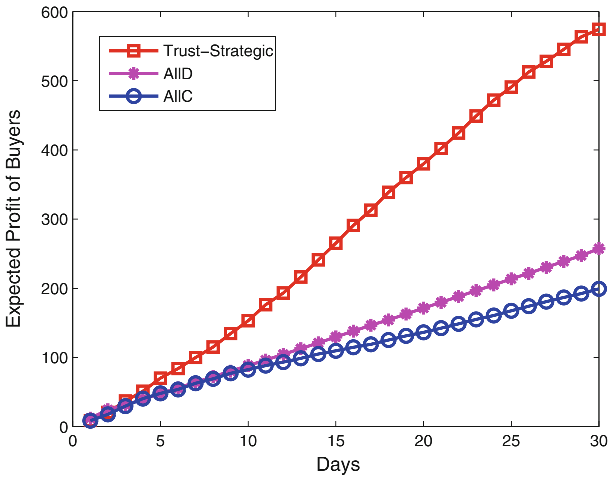

Fig. 4 The profit of different types of buyers where ALLD buyers occupy 70 % of the system

This type of buyers blindly share their truthful feedback with others but would not be treated the same by other types of buyers.

In Fig. 4 we plot the situation where the marketplace is mainly populated with ALLD buyers. We notice that trust-strategic buyers consistently acquire the highest profit. However, the ratio of their current profit in comparison with their profit obtained in the former case (presented in Fig. 3) is lower (less than one). Also, the obtained profit of ALLC buyers is rather similar to ALLD buyers. Since the environment is significantly populated with dishonest participants, buyers cannot access useful reputation information about sellers and thus cannot discover the sellers with the highest QoS.

Similar results can be seen in Fig. 5. This experiment considers the case where trust-strategic buyers take a major proportion in the competitive marketplace. Aside from the highest profit of trust-strategic buyers, interestingly we observe that the profit of ALLC

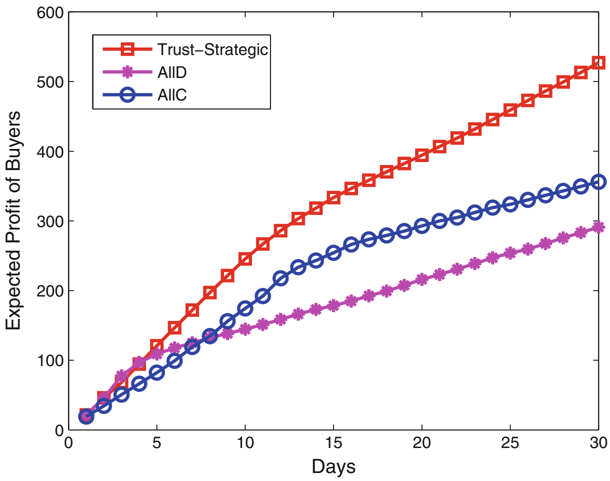

Fig. 5 The profit of different types of buyers where trust-strategic buyers occupy 70 % of the system

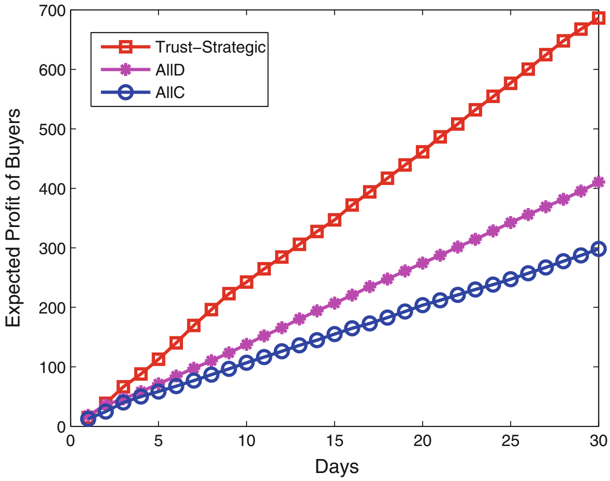

Fig. 6 The profit of different types of buyers where 40 % are ALLC, 40 % are ALLD and 20 % are trust-strategic in the system

buyers is higher than ALLD. The possible reason is that trust-strategic buyers would analyze and learn their behaviours as time passes and adopt an appropriate strategy to counter ALLC and ALLD buyers properly. Thus, they would share honest rating information with ALLC and act vice versa towards ALLD buyers.

From Fig. 6 we can observe that a major percentage of the population is dedicated to ALLC and ALLD buyers and that trust-strategic buyers are in the minority; however, this group of buyers is equipped with a mechanism to perform effectively in the system and gains the largest profits in comparison with their competitors.

Finally, Fig. 7 envisages the condition where different types of buyers are equally distributed in the marketplace. We notice that ALLC and ALLD buyers could only earn almost half of the profit that trust-strategic buyers gained. In Fig. 8, we demonstrate the average

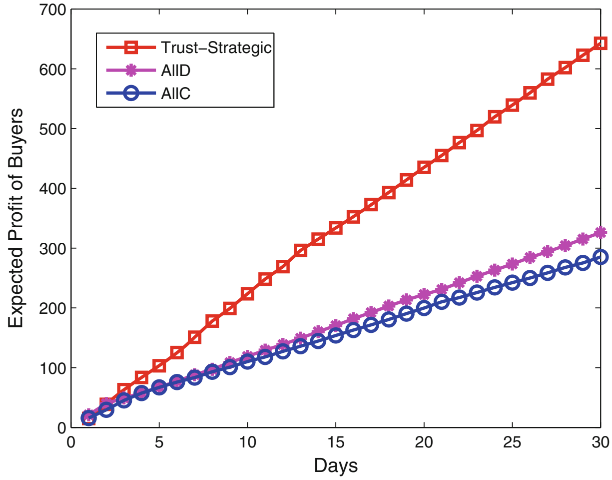

Fig. 7 The profit of different types of buyers in the balanced environment

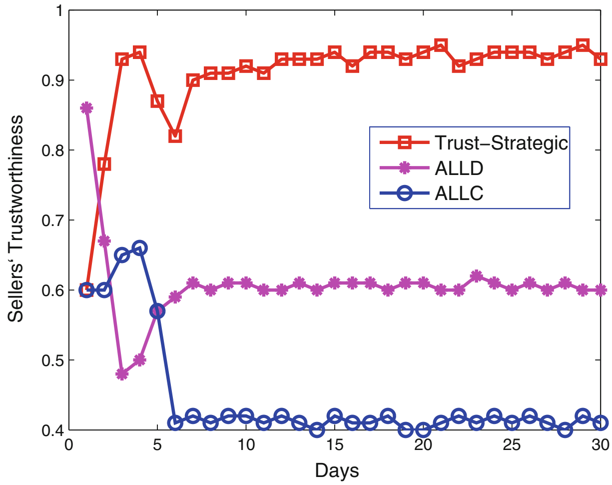

Fig. 8 Trustworthiness of sellers who have transacted with different buyers

trustworthiness of sellers with whom different types of buyers have done business in the balanced environment. It indicates that the buyers adopting the TOSR component can discover a significantly larger number of more trustworthy sellers to conduct business with.

In the above-mentioned experiments, we show that our proposed TOSR component provides buyers with the ability to obtain maximum profits compared to their rivals. We further observe that ALLC buyers who blindly share truthful information will gain the worst profit in most situations in the competitive e-marketplace.

Figure 9 shows the accuracy of trust-strategic buyers in predicting the expected utility of sellers. We notice that our mechanism enables such buyers to have more accurate predictions on the QoS that would be provided by their future transaction partners. As such, the deviation of the actual profit and the expected utility of sellers is minimum for the trust-strategic buyers.

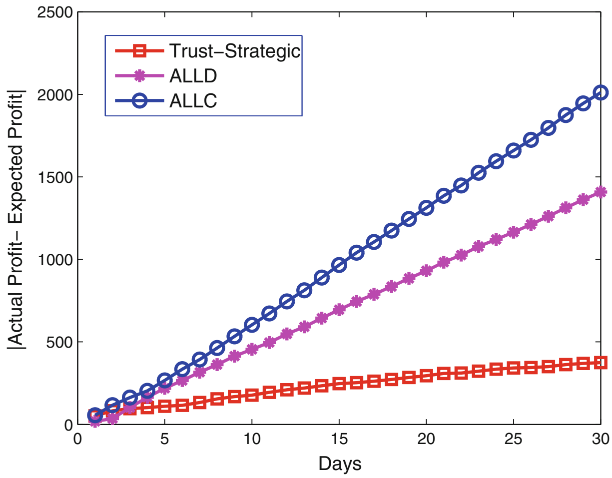

Fig. 9 The differences of the actual utility of buyers versus the predicted utility

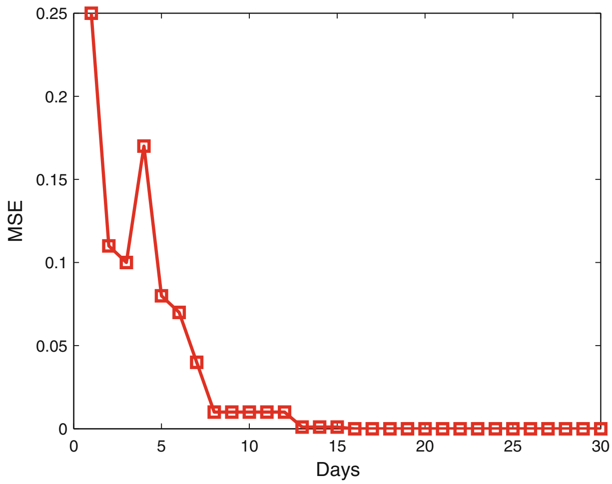

Fig. 10 The error rate of a buyer in predicting the actual willingness of advisers

5.2.2 The accuracy of modeling advisers' willingness

In this series of experiments, we first evaluate the accuracy of modeling 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 Fig. 10. The trust-strategic buyer initially assumes that the willingness of advisers is 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 ≈ 0. However, unlike the static behaviour of ALLC and ALLD advisers, trust-strategic advisers may adaptively change their behaviours from being honest

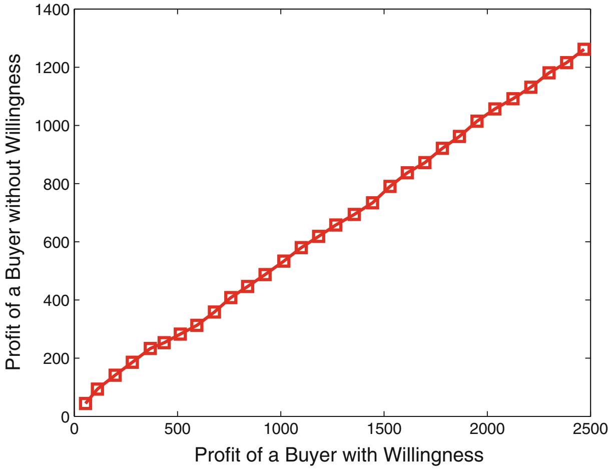

Fig. 11 Ratio of the expected utility of buyers with/without willingness factor

to being dishonest during the game where their benefits increase with lying. The bumping point (day four) illustrates this sudden change in the strategy of such a group of advisers in providing feedback, implying that their cooperation payoff drops below their defection payoff ($U_c < U_d$), so trust-strategic advisers alter their willingness from 1 to 0. This matter is initially hidden by trust-strategic buyers, so MSE significantly increases in round 4. However, we notice that the trust-strategic buyer is provided with a mechanism to capture such changes quickly and applies appropriate updates to the willingness of advisers so that the MSE proportionately decreases in subsequent days.

To evaluate the effectiveness of modeling the willingness of advisers in addition to their competency, we compute the expected profit of a group of trust-strategic buyers *with* modeling of their willingness (Eq. (3)) versus trust-strategic buyers *without* modeling of their willingness (i.e. Eq. (3) is changed to $T_r(a_i) = C_o(a_i)$). From Fig. 11, we can see that the obtained utility of the former group of buyers is significantly higher than the latter group of buyers 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 a competitive marketplace where advisers might behave maliciously despite their good competency. In Fig. 12, we further 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 business transactions with.

5.2.3 Validation of the TOSS component

To examine the significance of modeling the trustworthiness of sellers and filtering the dishonest ones, we design a set of experiments to illustrate negative consequences of allowing dishonest sellers to be involved in buyers' seller selection mechanism. We consider two different buyers: b_1 who models the trustworthiness of sellers and b_2 who does otherwise. In particular, we evaluate the TOSS model in two different settings. The first setting is the *realistic* case: the buyer b_1 does not have any personal experience with sellers and thus relies heavily on its advisers' opinions. In this case, b_1 uses the proposed TOSS model to detect trustworthy sellers. The second setting is the *naive* case, which corresponds to selection of

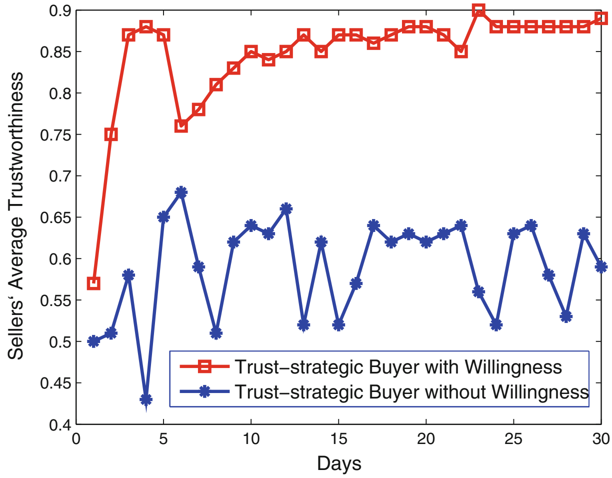

Fig. 12 The effect of the willingness factor in discovering highly-trustworthy sellers

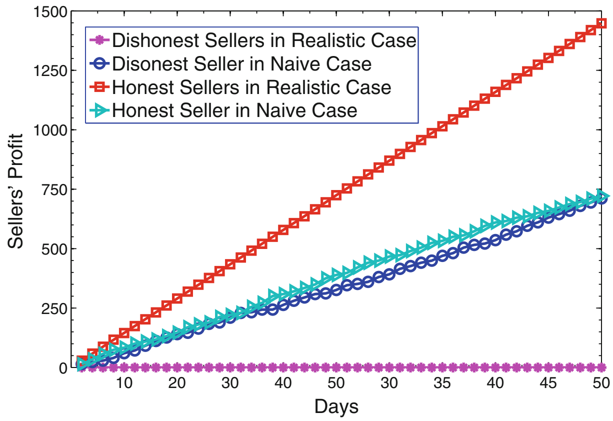

Fig. 13 The profit of sellers when 50 % are honest

sellers based only on the QoS values promised by sellers. In this case, the buyer b_2 utilizes the traditional multi-attribute FSBP auction to estimate potential profits without considering sellers' trustworthiness.

We plot the profit that the honest and dishonest group of sellers obtained in both settings. The results are shown in Figs. 13 and 14. We notice that, in the naive case when b_2 does not model the trustworthiness of sellers, deceptive sellers could gain larger profit than truthful sellers, especially when the majority of them are dishonest. Interestingly, this matter is reversed for the buyer b_1 in the realistic case. The buyer b_1 is provided with a means to evaluate the trustworthiness of sellers and filters out the dishonest ones so that the competition exclusively happens between honest sellers. We can observe that in the realistic case deceptive sellers do not find opportunity to conduct any business transaction with the buyer b_1.

The TOSS component treats sellers with varying trustworthiness values differently by giving sellers with a *higher* trustworthiness value the opportunity to bid *higher* QoS to buyers

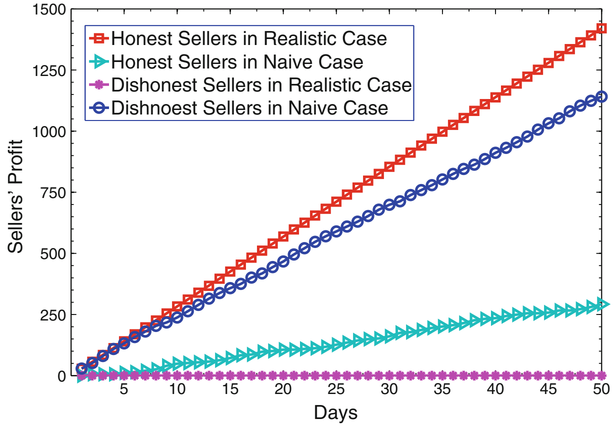

Fig. 14 The profit of sellers when 20 % are honest

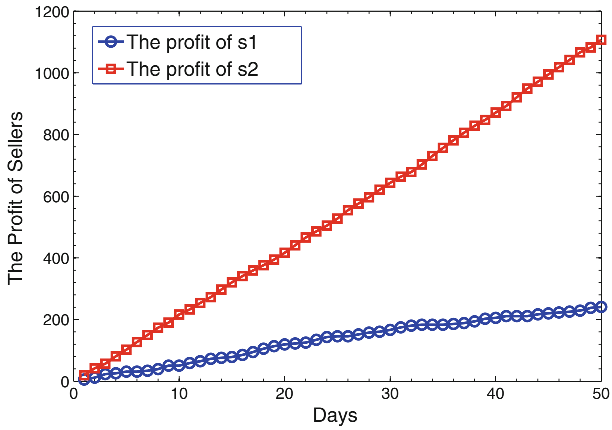

Fig. 15 The profit of seller s_1 vs. seller s_2

and increase their chance of winning the auction. This is achievable by making the actual preferences of buyers accessible to honest sellers. That is, the more trustworthy the seller, the closer the W gets to Ω. To empirically examine this, we conduct a specific experiment where seller s_1 with a trustworthiness of 0.7 and seller s_2 with a trustworthiness of 0.8 compete in the e-marketplace. As is noticeable in Fig. 15, even though the trustworthiness values of sellers are not significantly different from each other, their gained profits are considerably different. This is due to the fact that buyers distinguish sellers by differently announcing their preferences based on their trustworthiness so that the seller s_2 has a better chance to bid a higher QoS compared with the seller s_1.

5.2.4 The benefit of coping with seller dynamics

The final experiments in this section are dedicated to evaluate the significance of adopting the recency factor RF in the situation where sellers frequently change their behaviours. We depict the utility of different trust-strategic buyers with/without taking the dynamicity of sellers

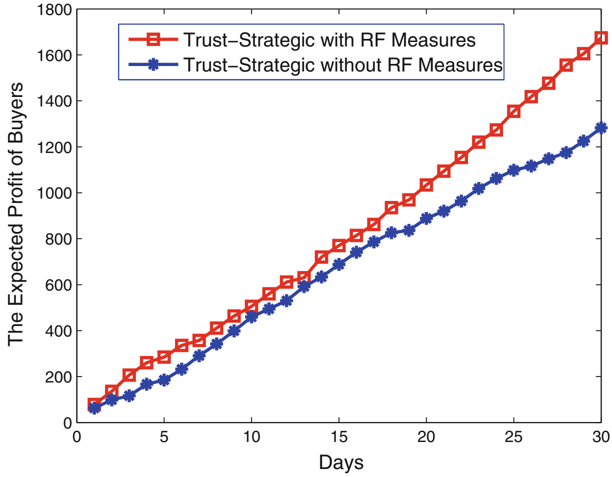

Fig. 16 The profit of trust-strategic buyers with high dynamicity in sellers' QoS

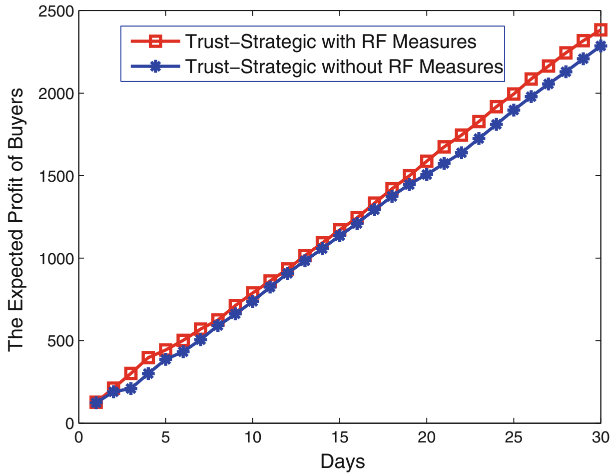

Fig. 17 The profit of trust-strategic buyers with low dynamicity in sellers' QoS

into account in two conditions: (1) sellers *highly* change their behaviours and (2) sellers *slightly* change their behaviours. The results are shown in Figs. 16 and 17, respectively. These figures demonstrate higher profits of trust-strategic buyers with the ability to discount the reputation reports of their advisers through RF in comparison with other trust-strategic buyers who do not consider the recency factor. Based on these modeling results, we can conclude that the recency factor could serve as a defensive mechanism against the changeability of sellers' behaviour.

To summarize, in the above experiments, we have shown that buyers adopting the TOSR component will be able to gain the largest profit in a competitive e-marketplace. This is because they will be able to conduct transactions with more trustworthy sellers and more accurately predict their expected utility compared with the buyers adopting other strategies. We further demonstrate that our proposed method of modeling advisers' willingness in reporting seller reputation information is accurate. Buyers modeling advisers' willingness will be able to gain larger utility through conducting business with more trustworthy sellers. In addition, we have shown that the proposed TOSS model creates incentives for sellers to act honestly, by excluding dishonest sellers from buyers' auctions and by allowing buyers to announce their QoS preferences differently pertaining to the sellers' trustworthiness values. Finally, the results illustrate that our mechanism works well even when sellers change their QoS over time.

5.3 Comparing with existing trust models

The existing trust models we compare with are TRAVOS, BLADE, the Personalized Approach and PRep. One common property shared by these trust models is that a buyer collects ratings (advice) from other buyers (advisers) and aggregates those ratings as well as the buyer's personal ratings. Then, the aggregated trust value helps buyers to make a better decision on which sellers to choose to conduct business transactions with. Therefore, these approaches are comparable with our proposed approach. The advice shared by buyers is the most recent ratings about the respective sellers. We equally divide the set of buyers into five groups: the first group would employ the proposed trust modeling approach, and the other groups implement the other four existing comparable trust models. The buyers in the five groups of our system model adviser trustworthiness and seller reputation based on the assigned approaches and choose a seller based on the proposed TOSS component. An adviser's credibility in providing advice is a value between [0.7, 0.9], following a Gaussian distribution with variance 0.02. Each buyer has some private information, which is drawn from a normal distribution, with the mean being the seller's QoS and variance being 0.02. In these comparative experiments, buyers would behave according to the characteristics of the competitive environment discussed in Sect. 5.1. More specifically, in the competitive environment, half of the buyers would provide seller reputation information according to their credibility, and the other half would always provide opposite advice. Meanwhile, in the semi-competitive environment, three quarters of the buyers provide advice according to their credibility, and the other quarter always provide opposite advice. Finally, in the non-

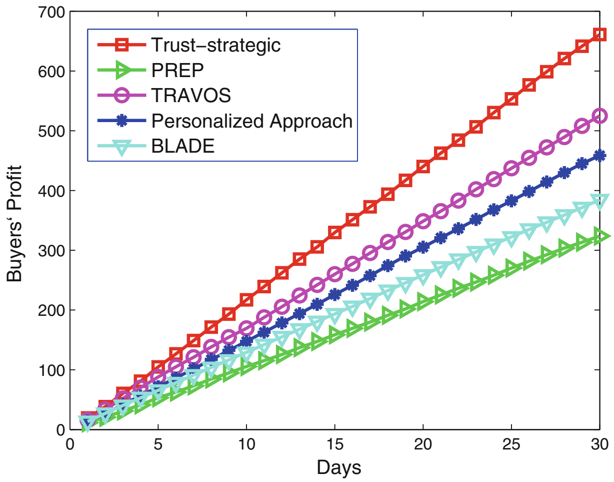

Fig. 18 The profit of buyers adopting different trust models in a competitive environment

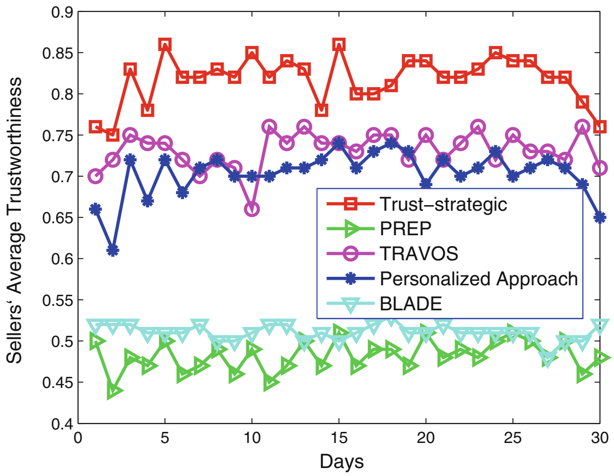

Fig. 19 The sellers' trustworthiness of buyers adopting different trust models in a competitive environment

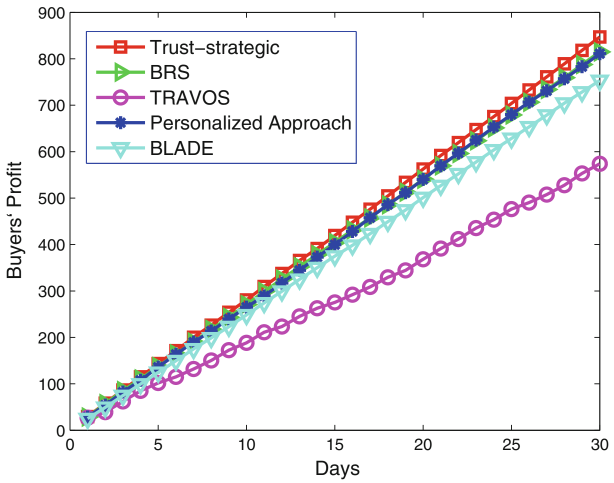

Fig. 20 The profit of buyers adopting different trust models in a non-competitive environment

competitive environment, all buyers in the last four groups would provide advice based on their credibility.

The profit of buyers in the five groups in a competitive environment is shown in Fig. 18 and the sellers' average trustworthiness modeled by the five groups of buyers is presented in Fig. 19. First, we can observe that buyers adopting our trust model outperform buyers in the other four groups. In the competitive environment, buyers in our trust model are trust-strategic and would only provide truthful advice for other buyers who had ever shared truthful advice with them. Therefore, the cooperation in providing truthful advice helps buyers to discover trustworthy sellers. On the other hand, being aware of the competition in the marketplace, trust-strategic buyers are unwilling to share truthful advice with dishonest advisers, which can mislead those advisers and create an advantage for themselves by successfully conducting transactions with honest sellers.

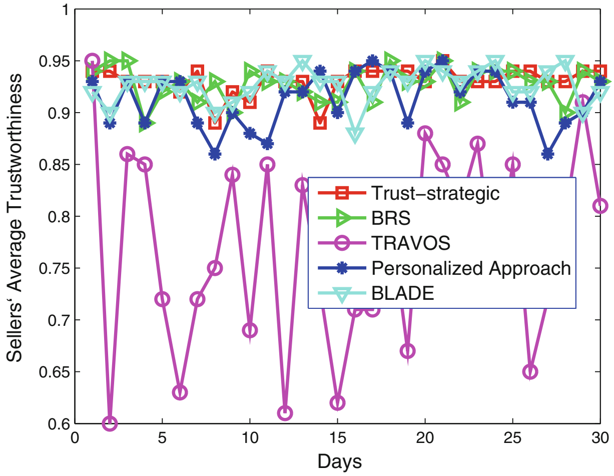

Fig. 21 The sellers' trustworthiness of buyers adopting different trust models in a non-competitive environment

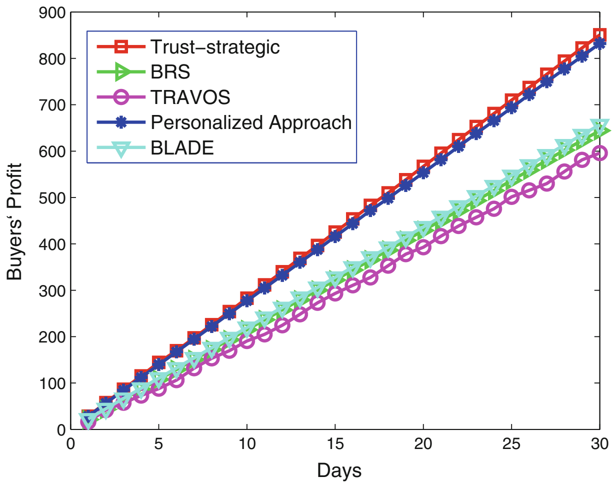

Fig. 22 The profit of buyers adopting different trust models in a semi-competitive environment

Second, the personalized approach and TRAVOS perform in the second tier. In the personalized approach, seller reputation is evaluated by combining private and public seller reputation together, and the public reputation is constructed only based on advisers' competency without considering advisers' willingness. However, in the competitive environment, competent advisers may provide untruthful advice, which makes the performance of the personalized approach worse than our model. In TRAVOS, buyers discount untruthful advice, and we also observe in our experiments that nearly 17 % of untruthful advice is discounted. As half of the advisers in TRAVOS are untruthful, TRAVOS can not discover all untruthful ratings, which makes its performance lower than our model. Third, BLADE and PRep perform the worst among the five models. In BLADE and PRep, buyers learn the Bayesian model of advisers in providing advice for each seller. However, sellers have only one item of

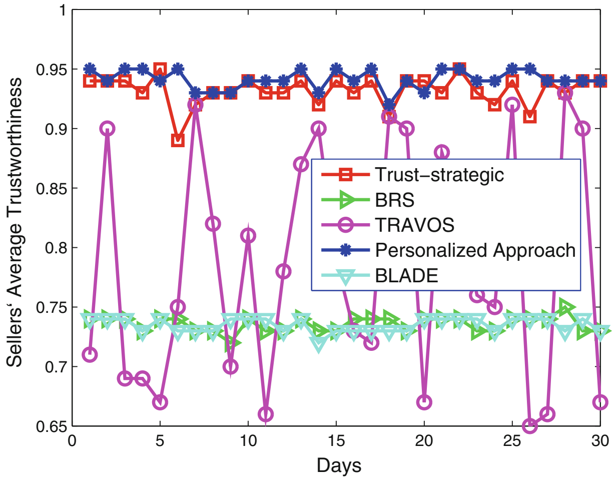

Fig. 23 The sellers' trustworthiness of buyers adopting different trust models in a semi-competitive environment

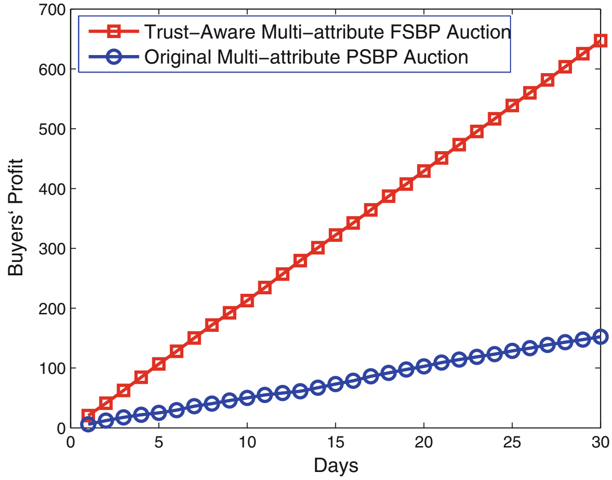

Fig. 24 The utility of buyers adopting different seller selection models in a competitive environment

inventory, which limits the learning accuracy and consequently buyers inaccurately rely on untruthful advice. Therefore, in the competitive environment, our model can perform more effectively than other trust models.

In the non-competitive environment, the profit of buyers and trustworthiness of sellers modeled by different groups of buyers are shown in Figs. 20 and 21 respectively. We can observe that all trust models, excluding TRAVOS, perform similarly in the non-competitive environment. Because there is no competition between buyers, advisers would provide advice according to their competency. Thus all models are able to select highly credible advisers and make a good seller selection. A possible reason for the lower performance of TRAVOS is that buyers adopting this trust model wrongly discount a portion of useful information

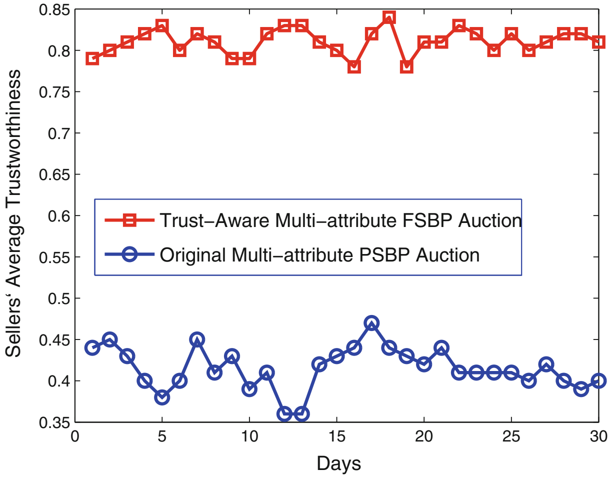

Fig. 25 The sellers' trustworthiness of buyers adopting different seller selection models in a competitive environment

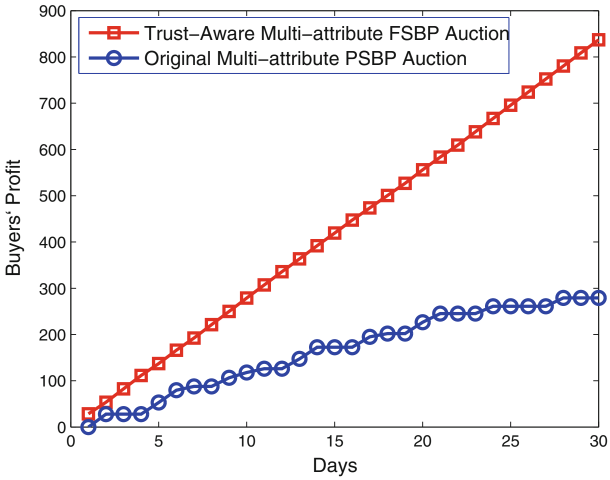

Fig. 26 The utility of buyers adopting different seller selection models in a non-competitive environment

(almost 17.3 % of truthful advice) so that they cannot effectively choose the most profitable sellers.

In the semi-competitive environment, the results are presented in Figs. 22 and 23. As we expected, the performance is between that in the competitive environment and that in the non-competitive environment. Our model can perform better than some approaches, but the advantage becomes smaller than the competitive environment due to the decreased competition in the e-marketplace.

To conclude, our trust modeling approach performs better than the other models. When the environment is more competitive, our model can present a larger advantage over others. Meanwhile, our model can achieve good performance in the non-competitive environment.

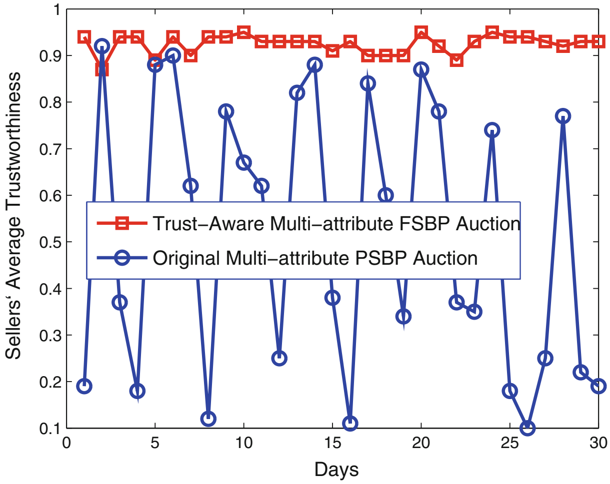

Fig. 27 The sellers' trustworthiness of buyers adopting different seller selection models in a non-competitive environment

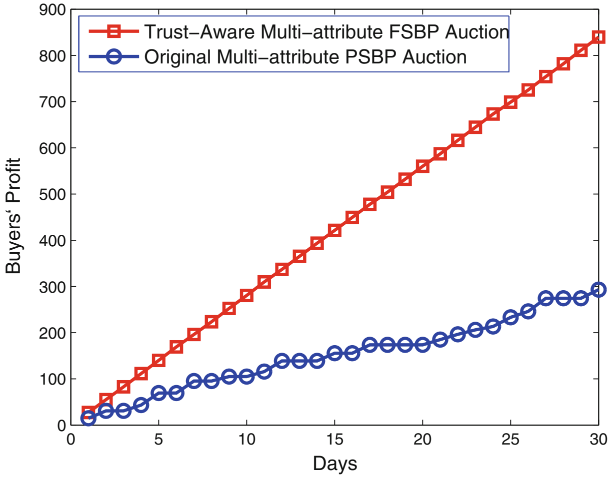

Fig. 28 The utility of buyers adopting different seller selection models in a semi-competitive environment

Therefore, our model can be effective at different levels of competition within electronic marketplaces.

5.4 Comparing with an existing seller selection approach

In this section, we present the experimental results of comparing the TOSS model with the traditional multi-attribute FSBP auction approach.

In the competitive environment, the utility of buyers who adopt different seller selection approaches is presented in Fig. 24, and the average trustworthiness of the selected sellers is shown in Fig. 25. We observe that buyers can achieve higher utility and conduct more profitable transactions by adopting the TOSS model. Our proposed approach enables buyers to make better decisions and avoids less trustworthy sellers by providing them with a mechanism

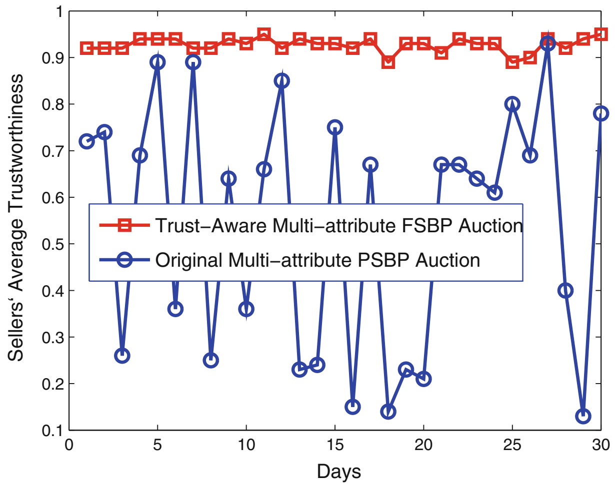

Fig. 29 The sellers' trustworthiness of buyers adopting different seller selection models in a semi-competitive environment

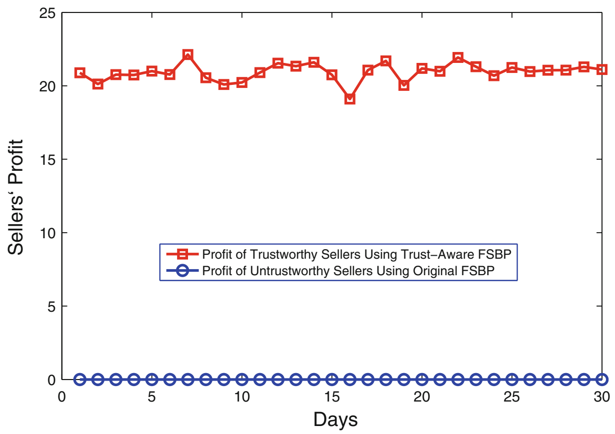

Fig. 30 The profit of different types of sellers in trust-aware FSBP auction

to preferentially reveal their preferences over various quality attributes of the products to different sellers.

In the non-competitive environment, the utility of different buyers who adopt different seller selection approaches and the trustworthiness of the selected sellers are presented in Figs. 26 and 27, respectively. We notice that buyers adopting the TOSS model can gain higher utility and conduct transactions with more trustworthy sellers than the traditional FSBP auction approach. Compared with the case in the competitive environment, buyers adopting the TOSS model can perform better in the non-competitive environment by achieving more utility and conducting transactions with highly trustworthy sellers. This happens due to the adequate inventory of highly trustworthy sellers in the non-competitive environment.

In the semi-competitive environment, the experimental results are shown in Figs. 28 and 29. The performance of the TOSS model in this type of environment is higher compared with the case presented in the competitive environment, but lower compared with the case presented in the non-competitive environment.

Finally, we observe that the profit of untrustworthy sellers is zero and the profit of trustworthy sellers is quite similar in all three types of environments as indicated in Fig. 30.[6] The reason for this phenomenon is that in our proposed seller selection approach, untrustworthy sellers are being filtered so that there is no chance for them to be selected as potential sellers by buyers. This provides incentives for sellers to behave honestly so as to increase their profits in all three environments with different degrees of competition.

To conclude, buyers adopting the TOSS model can achieve higher utility and choose more trustworthy transaction partners. Furthermore, sellers are shown to have incentive to be trustworthy regardless of their inventory.

6 Conclusions and future work

In this paper, we proposed a trust-oriented mechanism (TOSR model) for buyers in competitive e-marketplaces to strategically determine their reporting behaviours 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 IPD games. Buyers acquire reputation information regarding certain sellers from advisers and evaluate the quality of the received information through modeling of advisers' willingness and their competency levels. Based on the modeling results, buyers predict the expected utility of taking different reporting behaviours and choose the one that maximizes their utility.

In the trust-oriented seller selection component of our trust-oriented mechanism (TOSS model), buyers aggregate seller reputation information reported by advisers and the buyer's own personal experience with the sellers, to derive the trustworthiness of the sellers. Based on the modeled trustworthiness levels of sellers, buyers filter out the sellers whose trustworthiness values are not high enough. Then, they invite trustworthy sellers to join their trust-aware multi-attribute first-score sealed bid procurement auctions, and announce their QoS preferences on products to those sellers. After receiving bids from the sellers, the buyers will come up with the scores for different sellers. The seller with the highest score will be the winning seller.

We carried out different sets of experiments to verify the effectiveness of our proposed mechanism by simulating a competitive e-marketplace where buyers adopt different strategies of reporting seller reputation information and sellers may be malicious in delivering the promised products and also change their quality of products over time. Experimental results prove that our proposed trust-oriented mechanism provides a means for buyers to determine their optimal reporting strategy and achieve better utility. Furthermore, the results analytically confirm the value of the modeling of advisers' willingness in competitive e-marketplaces.

To examine the efficacy of our proposed approach in comparison with other existing trust models, we conduct various experiments for different types of environments such as competitive, semi-competitive and non-competitive environments. We compare the proposed trust modeling approach with four representative trust models: TRAVOS, BLADE, the Personalized Approach and PRep. The results show that our approach can outperform others in the sense that buyers adopting our proposed trust modeling method are able to gain more profit and transact with highly trustworthy sellers, especially in a competitive environment.

[6] That is the reason why we only show one figure to present the profit of sellers in different types of environments.

Finally, we compare the trust-oriented seller selection approach with the original FSBP auction approach. The results indicate that buyers can gain more utility and choose more trustworthy sellers by adopting our proposed approach, and sellers' incentives to be trustworthy has also been demonstrated.

In this paper, we seek to address the problem of seller selection, especially for competitive e-commerce systems where good sellers have limited inventory and buyers lack the personal experience to make decisions. The characteristics of such e-marketplaces enforce buyers to make a trade-off between sharing their truthful feedback with other buyers and discovering the profitable sellers who best meet their preferences. Thus, buyers should strategically determine the best behaviour, in order to maximize their profits. To the best of our knowledge there does not exist such a trust model in the literature, which consistently fulfils the features of the competitive e-marketplace. Our proposed approach differs from existing work by providing two main components: (1) an adviser credibility and willingness calculation mechanism and (2) a strategic reporting behaviour determination process. These components assist buyers to make an optimal decision in the proposed seller selection problem of such competitive e-commerce systems.

Furthermore, we picked the trust-aware multi-attribute FSBP auction model as our seller selection approach since it has the following three beneficial features. First, on one hand, buyers could communicate their preferences over different attributes of the product with sellers and on the other hand, sellers could aggregate buyers' requirements and bid the optimal price and quality attributes to the buyers. Secondly, since we further extend the FSBP auction model by incorporating the reputation value of sellers, we would provide buyers with a mechanism to determine the most profitable sellers considering both the detailed attributes of their QoS and their reputation value. This matter is mostly neglected in the literature of seller selection. Third, as the candidate set of sellers could be gathered through the FSBP auction where sellers bid for providing products, the seller selection procedure then could be naturally implemented.

For future work, we will evaluate the proposed model by considering more complex behaviours and environments. Also, evaluating the proposed approach with other seller selection approaches would be our future potential avenue of research. In addition, the proposed trust model is not currently applicable for new buyers who have no experience in evaluating the trustworthiness of advisers or sellers. For the new buyers, the initial trustworthiness is important and tricky to set, as an unsuitable initialization approach may cause existing buyers to leave and re-enter the system. Thus, we aim to design an additional scheme to help newcomers in choosing trustworthy advisers or sellers and meanwhile encourage them to stay in the system. Moreover, we will study how to create incentives for buyers to truthfully report seller reputation information in competitive e-marketplaces when buyers are trust-strategic. This is specifically more challenging than non-competitive e-marketplaces, because truthful reports are more costly. Furthermore, how to quantitatively measure the competition of a marketplace and the investigation on the impact of the competition to the incentive mechanism design remain to be addressed.

References

1. Berger, J. O. (1985). *Statistical decision theory and bayesian analysis*. New York: Springer-Verlag.
2. Chang, E., Hussain, F., & Dillon, T. (2005). *Trust and reputation for service-oriented environments: Technologies for building business intelligence and consumer confidence*. Chichester: Wiley.
3. Che, Y.-K. (1991). *Design competition through multidimensional auctions*. Working papers, Wisconsin Madison-Social Systems.

4. Comuzzi, M., & Pernici, B. (2005). An architecture for flexible web service QoS negotiation. In *Proceedings of the Ninth IEEE International EDOC Enterprise Computing Conference* (pp. 70–82).
5. David, E., Azoulay-Schwartz, R., & Kraus, S. (2002). Protocols and strategies for automated multi-attribute auctions. In *Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS'02* (pp. 77–85).
6. David, E., Azoulay-Schwartz, R., & Kraus, S. (2006). Bidding in sealed-bid and English multi-attribute auctions. *Decision Support Systems*, *42*(2), 527–556.
7. Haghpanah, Y., & Desjardins, M. (2012). PRep: A proabilistic reputation model for biased societies. In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems* (pp. 315–322).
8. Huynh, T. D., Jennings, N. R., & Shadbolt, N. R. (2006). An integrated trust and reputation model for open multi-agent systems. *Autonomous Agents and Multi-Agent Systems*, *13*(2), 119–154.
9. Jøsang, A., & Ismail, R. (2002). The beta reputation system. In *Proceedings of the 15th Bled Electronic Commerce Conference* (pp. 41–55).
10. Jurca, R. (2007). *Truthful reputation mechanisms for online systems*. PhD thesis, EPFL.
11. Khosravifar, B., Bentahar, J., Moazin, A., & Thiran, P. (2010). On the reputation of agent-based web services. In *Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence (AAAI)* (pp. 1352–1357).
12. Mui, L., Mohtashemi, M., & Halberstadt, A. (2002). A computational model of trust and reputation for e-businesses. In *Proceedings of the 35th Annual Hawaii International Conference on System Sciences* (pp. 2431–2439).
13. Nina Mazar, D. A., & Amir, On. (2008). The dishonesty of honest people: A theory of self-concept maintenance. *Journal of Marketing Research*, *45*(6), 633–644.
14. Noorian, Z., Marsh, S., & Fleming, M. (2011). Multi-layer cognitive filtering by behavioral modeling. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS)* (pp. 871–878).
15. Noorian, Z., Marsh, S., & Fleming, M. (2011). Prob-Cog: An adaptive filtering model for trust evaluation. In I. Wakeman, E. Gudes, C. Jensen, & J. Crampton (Eds.), *Trust Management V. IFIP Advances in Information and Communication Technology* (Vol.358, pp. 206–222). Boston: Springer.
16. Noorian, Z., & Ulieru, M. (August 2010). The state of the art in trust and reputation systems: A framework for comparison. *Journal of Theoretical and Applied Electronic Commerce Research*, *5*, 97–117.
17. Regan, K., Poupart, P., & Cohen, R. Bayesian reputation modeling in e-marketplaces sensitive to subjectivity, deception and change. In Proceedings of the 21st National Conference on Artificial Intelligence.
18. Smith, M. J., & Desjardins, M. (2009). Learning to trust in the competence and commitment of agents. *Autonomous Agents and Multi-Agent Systems*, *18*, 36–82.
19. Strecker, S., & Seifert, S. (2004). Electronic sourcing with multi-attribute auctions. In *Proceedings of the 37th Annual Hawaii International Conference on System Sciences (HICSS'04)* (pp. 701–712).
20. Teacy, W. T. L., Patel, N. R. J. J., & Luck, M. (2006). TRAVOS: Trust and reputation in the context of inaccurate information sources. *Journal of, Autonomous Agents and Multi-Agent Systems*, *12*(2), 183–198.
21. Teacy, W. T. L., Luck, M., Rogers, A., & Jennings, N. R. (2012). An efficient and versatile approach to trust and reputation using hierarchical bayesian modelling. *Artificial Intelligence*, *193*, 149–185.
22. Vidal, J. (2001). *Fundamentals of multiagent systems with NetLogo examples*. Cambridge: MIT Press.
23. Vignaux, G. (2004). *Multi-attribute decision problems*. Technical report, Victoria University of Wellington, New Zealand.
24. Wang, Y., Singh, M. P. (2007). Formal trust model for multiagent systems. In *Proceedings of the 20th International Joint Conference on Artifical, Intelligence* (Vol. 7, pp. 1551–1556).
25. Xiong, L., & Liu, L. (2004). PeerTrust: Supporting reputation-based trust for peer-to-peer electronic communities. *IEEE Transactions on Knowledge and Data Engineering*, *16*(7), 843–857.
26. Yu, B., & Singh, M. P. (2003). Detecting deception in reputation management. In *Proceedings of the Second International Joint Conference on Autonomous Agents and Multiagent Systems, ACM* (pp. 73–80).
27. Zhang, J. (2009). *Promoting honesty in electronic marketplaces: Combining Trust modeling and incentive mechanism design*. PhD thesis, University of Waterloo.
28. Zhang, J., & Cohen, R. (2013). A framework for trust modeling in multiagent electronic marketplaces with buying advisors to consider varying seller behavior and the limiting of seller bids. *ACM Transactions on Intelligent Systems and Technology (ACM TIST)*, *4*, 1–22.