AN ADAPTIVE REPUTATION-BASED TRUST MODEL FOR INTELLIGENT AGENTS IN E-MARKETPLACE

by

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ABSTRACT

AN ADAPTIVE REPUTATION-BASED TRUST MODEL

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IN E-MARKETPLACE

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In the emerging Electronic Marketplace, intelligent agents that are reactive, proactive and social will become the major players. These intelligent agents will search for good deals, evaluate trading partners and eventually provide advice on or even make decisions on transactions for their principals. To this end, it is vitally important for the agents to be able to precisely estimate the trust of the business partners to make successful deals. This dissertation proposes an adaptive reputation-based trust model which can be utilized by intelligent agents in an open Electronic Marketplace, where the seller agents and buyer agents can enter and leave the market freely and the service

quality and price of goods vary. The trust model is based on an agent's reputation history, witness testimony, and other weighting factors. Learning is integrated to make the trust model adaptive and robust in a dynamic environment. To verify the proposed adaptive reputation-based trust model and the significance of the constructs and factors of the model and to compare the performance of the proposed model with other models, a multi-agent system is built to simulate the interactions among these agents.

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CHAPTER 1

INTRODUCTION

1.1 Problem to Solve

In the Electronic Marketplace (E-Marketplace), intelligent agents that are reactive, proactive and social, will become the major players. These intelligent agents will search for good deals, evaluate the trustworthiness of the trading partners, negotiate with potential business partners and eventually provide advice on, or even make decisions on, transactions for their human principals. This will dramatically reduce their human principals' online shopping burden as mentioned in following sections. This thesis develops a reputation-based trust model that is adaptive and robust in a dynamic environment. Since trust is one of the essential elements in any business transaction, it goes without saying that the outcome of the trustworthiness estimation of potential business partners influence other tasks in the six fundamental stages (Guttman, Moukas & Maes, 1998) guiding the buying behavior, such as agents searching for good deals, transaction negotiation and making with-who and at-what-price decisions.

In the following sections, a detailed introduction concerning concepts and the research background of E-commerce, the agents, intelligent agents, multi-agent systems, trust and reputation is given.

1.2 E-commerce

E-commerce is a useful tool to connect business partners in a virtual supply chain to reduce the costs and cut time (Stair & Reynolds, 2006). It offers new channels, business opportunities, and enables new business models for buyers and sellers to effectively and efficiently conduct business over the Internet. For example, Dell's business model of selling computers online has enabled Dell to excel among its peers; and eBay and Amazon have utilized their E-commerce models to become the leaders in the business of personal auctions and the online bookstore business, respectively. Compared with traditional marketplaces, consumers gain more power in searching for, comparing, and buying goods or services online and online consumers can benefit from online feedback quickly and conveniently. Without stepping out of their door, consumers can compare the price of the same product from different merchants online more efficiently and effectively; consumers can pay for the product online and have it delivered to their door in a day or two. Meanwhile, suppliers also benefit from E-Marketplaces. These benefits include greater access by their consumers online. Suppliers can also avoid brick-and-mortar stores and save rentals. They can maintain inventory and pricing faster compared with the traditional marketplace. Both buyers and sellers have the opportunity to trade with a larger set of trading partners compared with the traditional marketplaces (Bolton, Katok & Ockenfels, 2004). The E-commerce ComScore, a global Internet information provider, forecasts the total E-Commerce spending by consumers will reach approximately $170 billion in 2006. As stated by Gian Fulgoni, Chairman and Co-Founder of comScore Networks, "Growth in non-travel

online spending continues at a rate of 25 percent year-over-year, which suggests that consumers' online purchase behavior has been relatively unaffected by the general economic trends (comScore, 2006)." "Based on the first-half growth rate, total U.S. online consumer spending is on track to reach $200 billion in 2007 (comScore.com, 2007)."

When an on-line transaction is successfully fulfilled, that is, when the buyer receives exactly what he is promised and the seller receives the due payment, it is a win-win scenario. In this case, both sides are satisfied and the E-Marketplace will flourish. But when either side or both sides cheat, the disappointed side will exit the E-Marketplace and choose other means to do business. Consequently the E-Marketplace will die. Trust plays a significantly important role in the marketplace and especially in the E-Marketplace where buyers and sellers may never see each other and may only do business once with that consumer or provider. How can a buyer pay some seller he has never seen in a one-time transaction for something he cannot inspect until after it is paid for and delivered? Trust is the key; as stated, "trust is of much importance precisely because its presence or absence can have a strong bearing on what we choose to do and, in many cases, what we can do (Dasgupta, 1988)." In an E-Marketplace with intelligent agents, trust still plays a very important roll in the selection of business partners.

1.3 Agents, Intelligent Agents and Multi-agent Systems

1.3.1 Agents, Intelligent Agents and Multi-agent Systems

There is no universally accepted definition of the term "agent." However, by some definitions from extant research in this field we can get a sense of it. An agent is an entity that can be viewed as perceiving its environment through sensors and acting upon its environment through effectors (Russell & Norvig, 1995). Agents are the systems that can decide for themselves what they need to do in order to satisfy their design objectives (Weiss, 1999). The agent is a natural extension of streams in the history of programming, communication and control. It is synthetic of information from a wide collection of disciplines, such as organization theory, language theory, economics, and psychology, among others (Gasser & Briot, 1998). In a nutshell, an agent is an encapsulated unit of computer codes that can perform some actions based on "its" own decisions to meet the design needs automatically. An intelligent agent is an agent that is capable of flexible autonomous actions in order to meet its design objectives. Flexibility is the key to demarcate the intelligent agent from other agents, which means the ability of being reactive, proactive and social. A reactive agent should be able to perceive the environment and respond in a timely fashion to changes to satisfy its design objectives; a proactive agent should be goal-directed and take the initiative to satisfy its design objectives; a social agent should interact with other agents, even humans, to satisfy its design objectives (Wooldridge & Jennings, 1995). Other properties can be added to the intelligent agent based on needs such as the property of learning, adoption, rationality, and belief. These features are highly appreciated by

researchers in social science. Since humans are involved in the social phenomena, they have their own belief, desire and intension. They are also interactive, proactive and social. Agents can learn from their experiences. Intelligent agents, due to their above-mentioned characteristics, can adequately simulate human actors in many social phenomena.

The power of the individual intelligent agent is very limited in formulating complex problems and in processing information by its knowledge, its computing resources and its perspective (Simon, 1957). A more powerful complex agents system, the multi-agent system (MAS), is formed when the intelligent agents were able to interoperate and coordinate with each other. MAS has existed as a subfield of Artificial Intelligence for less than two decades. Sycara (Sycara, 1998) designates the characteristics of MAS as follows:

- Each agent's information or capacities for solving the problem is incomplete,
- No global control system,
- Data are decentralized, and
- Computation is asynchronous.

The agents are not necessarily homogeneous. They can be implemented according to the design requirements and different beliefs, resources and knowledge can be coded in different agents if necessary. MAS can be classified into four categories: the Homogenous Non-Communicating MAS, the Heterogeneous Non-Communicating MAS, Homogenous Communicating MAS and Heterogeneous Communicating MAS

(Stone & Veloso, 2000). MAS can be applied to simulate different scenarios with different settings.

1.3.2 Contemporary Uses of MASs

Axtell (Axtell, 2000) posits that there exist three distinct uses of agent-modeling techniques in social science. The first use is in the case of the existence of either analytically or numerically solvable equations. The second use is when a mathematical equation is available but not solvable, and the third use is when there is no mathematical equation modeling at all. For the first use, MAS can give researchers visual output to demonstrate the modeling. The second use of MAS can provide researchers some insight into the functioning of the model. The third use of MAS solves the problem which cannot be solved otherwise, for example, in the case where MAS is used to play the MIT Beer Game (Sterman, 1989) and optimal policies are discovered and the Bullwhip effect is eliminated, which is not achievable by analytical solutions (Kimbrough et al., 2002).

In experimental labs, intelligent agents by default are honest and cooperative. But in many real-life settings, agents will not necessarily cooperate with one another (Yu & Singh, 2002). Especially in E-Marketplace settings, intelligent agents actually act on behalf of their corresponding principals, or human agents. They are all rational, opportunistic, and goal-oriented. There can be strategic sellers and buyers who change their business strategies and try to gain the most by taking advantage of the shortcomings of an existing E-Marketplace.

1.4 E-commerce and Agents

As mentioned, consumers have reaped many benefits using E-Marketplace rather than by trading in the traditional marketplace. Despite all the advantages of the E-Marketplace, online consumers still have to do much to conduct an E-commerce transaction. In order to get a favorable price, online consumers have to search on line by their own efforts. In order to learn about their transaction partner's trustworthiness and reliability, they must read feedback and numerous diverse scores. Still the partner's reliability is not guaranteed. In order to bid on an auction, they must continue to monitor the entire process of the auction. Online consumers are required to interact with E-Marketplace intensively to conduct online transactions, spending much time and facing many burdens.

By summarizing the available descriptive theories and models which attempt to capture consumers' buying behavior, Guttman et al. (Guttman, Moukas & Maes, 1998) recognize six fundamental stages guiding the buying behavior, which are

- need identification, in which the consumer is aware of unmet needs;
- product brokering, in which the consumer retrieve information to determine what to buy;
- merchant brokering, in which the consumer decides from whom to buy based on the outcome of previous phase and merchant alternatives' price, and reputation,;
- negotiation, in which the terms of transaction are determined;
- purchase and delivery, in which merchandise is paid for and delivered; and

- service and evaluation, in which the post-purchase service and evaluation of the customer satisfaction are conducted.

For the product brokering stage, currently online consumers can use diverse search engines, such as google.com and yahoo.com, to search and compare the price of the same product. There are also websites, such as epinion.com, that provide the online consumer with comprehensive product search, price comparison, and consumer feedback.

In pre-Internet societies, people relied on word-of-mouth to select reputable business partners. Word-of-mouth emerged naturally and evolved in ways that were difficult to control or model (Dellarocas, 2003). At the time, dishonest sellers could easily do one-shot business here and there without failure. In the Internet era, digitized word-of-mouth can be spread more widely and rapidly. In the E-Marketplace, the digitized word-of-mouth, the feedback mechanism, can deter one-shot interaction if sellers have to maintain the same ID life long. That is, if a seller cheats in one interaction, consumers' word of his misdeed will spread in the E-Marketplace quickly and informed consumers will not be willing to do business with that seller .

1.4.1 Reputation and Trust

There are numerous definitions for reputation and trust. In order to study and model the two concepts, clear definitions of both concepts are needed.

1.4.1.1 Trust

Trust is vitally important in people's everyday life. "The importance of trust pervades the most diverse situation … from marriage to economic development, from

buying a second-hand car to international affairs (Gambetta, 1988b)." The importance of trust draws more and more attention from researchers in diverse research fields. Dasgupta (Dasgupta, 1988) talks about trust in the sense of "correct expectations about the actions of other people that have a bearing on one's own choice of action when that action must be chosen before one can monitor the actions of those other." Luhmann (Luhmann, 1979) states that "Trust, in the broadest sense of confidence in one's expectations, is a basic fact of social life." He discusses trust in terms of reduction of complexity and points out that in cooperative actions or coordinated actions, trust can reveal the possibility of actions which may not be attractive or attainable without trust in place. Gambetta (Gambetta, 1988a) gives a summarized definition of trust as "trust (or, symmetrically, distrust) is a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action, both before it can monitor such action (or independently of its capacity ever to be able to monitor it) and in a context in which it affects its own action." Hardin (Hardin, 2001) clarifies the trust and trustworthy. That is, if everyone with whom we interact is trustworthy, we trust everybody; and if the society is full of people who lack trustworthiness, we would not trust anyone. Like the scenario in the classic "Prisoners' Dilemma" game, when the two prisoners cooperate, they can maximize their social welfare, which is the sum of all agents' payoffs or utilities in a given solution. Only when there is trust between them, can they think of cooperation under the pressure of severe penalty of defection by either side or both sides.

Trust is a multifaceted and very rich concept. By reviewing existing work, McKnight and Chervany (McKnight & Chervany, 1996) find three major categories of trust construct types. They are Impersonal/Structural trust, Dispositional trust and Personal/Interpersonal trust. In addition, sixteen attribute dimensions, referred to as the trust construct types, are recognized. These attribute dimensions are benevolence/ caring/concern, competence, goodwill/good intentions, honesty, expertness, dynamism, predictability, goodness/morality, responsiveness, credibility, reliability, dependability, openness/open-minded, careful/safe, shared understanding, personal attraction. The first four dimensions are frequently mentioned by researchers.

Pavlou and Gefen (Pavlou & Gefen, 2004) study institution-based trust in the E-Marketplace with the involvement of consumers in the transactions. Institution-based trust falls into the category of Impersonal/Structural trust stipulated by McKnight and Chervany. The institution-based trust mechanisms include Feedback Mechanism, Escrow Services, Credit Card Guarantees, and Trust in Intermediary, i.e. the specific online marketplace itself. This work finds that these mechanisms engender the buyer's trust in the community of auction sellers.

We perceive that the study of the effect of trust in its full extent in the E-Marketplace, i.e. to subsume all the trust construct types in the study, can render better understanding of the trust in the E-Marketplace. So far no such work has been done. There in no research that attempts to tackle the interrelations between the three trust construct types, and the relationship between trust and its closely related concepts, such as reputation, and reciprocity.

1.4.1.2 Reputation

Reputation is closely related to trust and it is quite often confused with the concept of trust. Literally speaking, reputation means "good name" in a certain domain. Mui et al. (L. Mui & Halberstadt, 2002) define reputation as perception that an agent creates through past action about its intentions and norms. In this definition of reputation, Ostrom's (Ostrom, 1998) definition of norm is adopted as " … heuristics that individuals adopt from a moral perspective, in that these are the kinds of actions they wish to follow in living their life." In order to unify the concepts about reputation used by different researchers in the Distributed Artificial Intelligence, economics, and evolutionary biology, an intuitive typology is proposed as depicted in figure 1.1. According to this work of Mui et al., reputation is a contextual quantity.

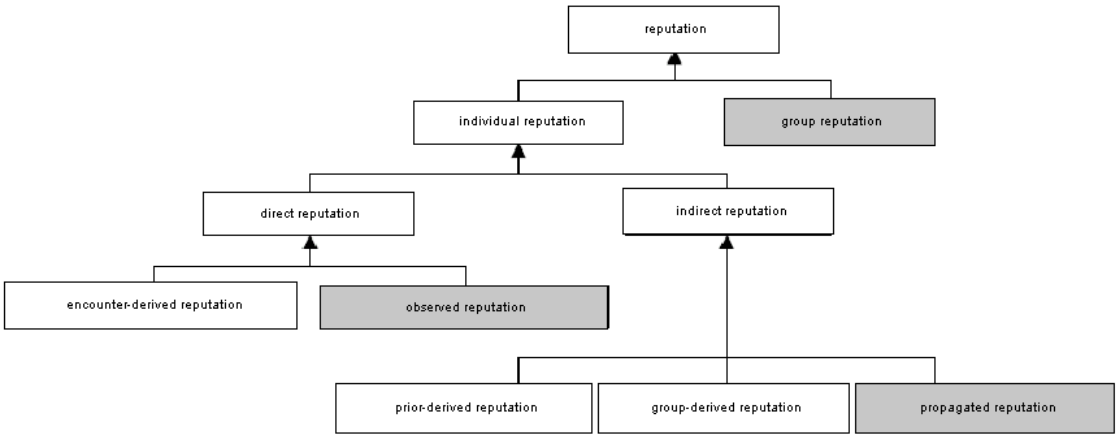

Figure 1.1 Reputation Typology Adapted from Mui et al.
(Mui, Halberstadt & Mohtashemi, 2002)

Derived from individual reputation and/or group reputation, reputation can be used to describe an individual or a group of individuals. Individual reputation can be derived from direct reputation and/or indirect reputation. Direct reputation can be derived either

from direct encounters or observations. To evaluate a seller's reputation based on eBay's feedback postings about the seller is an example of observed reputation. Indirect reputation is inferred from the collected indirect information. The indirect reputation can be derived from prior-derived reputation, which is based on prior beliefs or discriminatory priors about strangers, and newcomers; the group-derived reputation which is the reputation inference about one agent based on the priors of the group it belongs to; and propagated reputation based on the reputation information passed by other agents. Sabater et al. (Sabater & Sierra, 2005) perceive reputation as one of the elements that helps to build trust on others.

In summary, reputation and trust are highly correlated concepts, and reputation is one important element that affects the building of trust with others. There are multiple information sources for an entity to form another's reputation. An entity's reputation can be a good predictor of other entities' trust in it.

1.4.2 Pseudonym

Currently, the majority of the E-Marketplaces requests that users have their own user identities and passwords. Usually the pseudonyms are used as the user identities. Users are free to stop using one set of user identity and password and to start with another set of user identity and password. But an easily modified pseudonym system creates the incentive to misbehave without paying the reputation consequences (Friedman & Resnick, 1998). However, the identity changer has to pay a penalty as a new trader whose reputation must be built from scratch and over time. This penalty can be viewed as the switching cost in the E-Marketplace research.

1.4.3 Other Agent-based Systems in E-Commerce

Park and Park (Park & Park, 2003) propose an agent-based system for merchandise management which performs evaluating and selecting merchandise and predicting seasons and building purchase schedules autonomously in the B2B E-Commerce environment. The system fulfills the first two phases of the buying cycle in merchandise management, proposed by Mason et al. (Mason, Mayer, & Ezell, 1991) which includes Determining Needs Phase, Follow-up Phase, Select Supplier Phase and Negotiate Purchase Phase. Park's agent-based merchandise management system is composed of three agents and one module, i.e., Needs Determining Agent, Follow-up Agent, Supervisor Agent and Season Period Updating Model, respectively. By using the Data Envelopment Analysis, Genetic Algorithm, Linear Regression and Rule Induction Algorithm, the system can accomplish merchandise management tasks timely and autonomously. It can reduce the inventory level and increase sales and profits. Merchandise management by intelligent agents will be important in B2B E-Commerce, since intelligent agents should conduct most transactions such as selecting suppliers and negotiating which until now have been performed by a human being (Park & Park, 2003). The proposed adaptive reputation-based trust model in this dissertation, which provides estimated trust of the agents in E-Commerce, can be an indispensable component to build the Supplier Selection Agents to fulfill the tasks for the Select Supplier Phase.

1.5 Research Contributions

In theory development, first a trust theory which is oriented to intelligent agents is built with the computer simulation methodology as the validation means. The trust between humans has different characteristics compared with that between intelligent agents. The proposed trust model singles out the relevant constructs and factors to build the trust model for the intelligent agent, inspired by the trust theories and empirical findings about humans and extant research about intelligent agents. This research also enhances the trust theories among humans. For example, the trust theories for humans have not adopted the price-volume factors in modeling human trust which can actually be an important factor. Second, a new and better reputation-based trust model is proposed for the intelligent agent in E-commerce and has the potential to be used to model the trust between human agents and between the intelligent agent and the human agent. Third, the model is parsimonious. It only uses the basic transaction data in current E-Marketplaces such as price, volume, feedback ratings, and time stamps This model takes into consideration the temporal-effect factor, the positive-negative-impact factor and price-volume factor in the trust and reputation estimation. Fourth, the proposed model is built on the extant research and the latest empirical findings of research in the E-commerce field and Distributed Artificial Intelligence field which is interdisciplinary. Fifth, the model provides a good example of modeling the desire, belief, and intention of intelligent agents in the E-commerce context which contributes to the intelligent information systems and next generation E-commerce. More research should be conducted to embrace intelligent information systems which utilize AI to

further reduce the decision making burdens of human beings so as to help people with more flexible and sound decisions.

The contributions to the practitioners can be six-fold. First, the proposed reputation-based trust model is a better practical model for trust evaluation in the E-commerce. The model provides the E-Marketplace designers and managers with a practical design guideline of the major players of E-Marketplaces. Due to its parsimonious characteristic (i.e. the proposed model only utilizes the commonly available transaction data of the current E-Marketplaces without destructive change of the current E-commerce infrastructures), the proposed trust model can be calculated based on the commonly available transaction data. Second, since the learning mechanism is adopted, the proposed reputation-based trust model is robust and adaptive in the inherent noisy and dynamic E-Marketplace environment, shrugging off unrealistic assumptions made by former research. Third, the difference between the estimated trust value and the rating of the immediate transaction is utilized in the reputation-components-combination weight learning for the first time. The transaction data are used fully to deduce more valuable information. Fourth, practitioners in E-commerce have a new trust model in hand to summarize the trust of the sellers and buyers regardless of whether they are human agents or intelligent agents. Fifth, the implementation of the proposed model can reduce the online consumers' data processing burden and increase information accuracy even in the current E-commerce settings; that is, human agents have to read each feedback and diverse scores about each potential business partner to estimate their trustworthiness. The proposed reputation-

based trust model produces a better comprehensive single estimated trust value for each potential business partner which integrates the feedback ratings and diverse scores. This approach saves time for the online consumer to read the piece-meal data of each potential business partner, reduces their information processing burden, and improves the trustworthiness estimate accuracy. Sixth, the model makes the trust comparison among multiple potential business partners more accurate and practical and also facilitates the automated decision makings.

1.6 Organization of This Study

Chapter two presents a historical perspective of the typical trust or/and reputation models in this research area. Their drawbacks are discussed. The proposed adaptive reputation-based trust model is presented in chapter three. Chapter four begins with the discussion of the simulation methods' validation in theory development and is followed by system design of the MAS which is to be used to simulate an E-Marketplace, and finally concludes with detailed simulation and testing plans, the simulation results and conclusions.

CHAPTER 2

LITERATURE REVIEW

2.1 Review of Trust and Reputation Models

There are many computational models of trust and reputation that are in the multi-agent research arena.

2.1.1 Traditional Reputation Model

Many E-Marketplaces provides the online consumers with the ratings of buyers or of sellers or both. For most of the cases, transaction partners can rate each other using. A rating indicates how satisfied or dissatisfied a buyer or a seller is with a online transaction with its counterpart after a transaction. In fact, rating is an implementation of reputation.

Amazon.com provides a rating system of five-pointed scale, the star rating system. The transaction partners are rated from five stars (best) to 1 star (worst). The feedback rating of a designated seller is the average of feedback ratings submitted by buyers. This is a typical example of the traditional reputation model. Figure 2.1 is a snapshot of the profile of a member seller with Amozon.com (Amazon.com, 2007).

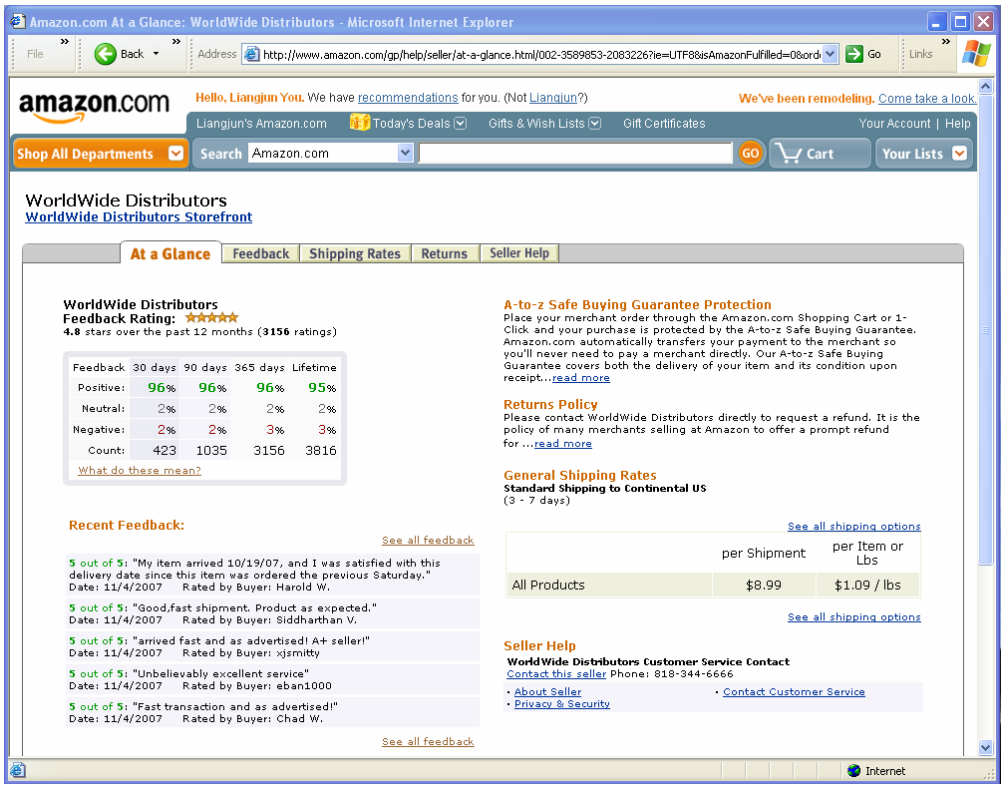

Figure 2.1 Amazon Member Profile Adapted from Amazon (Amazon, 2007)

The rating system of eBay is well-known in this research area. EBay is one of the most popular E-Marketplaces in the world. Up to now, eBay offers more than twenty localized sites worldwide covering Asia, Europe and North America. On any given day, there are millions of items available through auction-style and fixed-price trading (eBay, 2007). The items listed vary from cheap items such as books and toys to expensive items such as vehicles and real estate, including more than 30 categories. After each transaction via eBay, the buyer and the seller can rate each other on how well they conduct the transaction by leaving ratings and short feedback comments about the transaction. The ratings can be positive, neutral or negative. Each positive or

negative feedback adds or decreases one point from the evaluated member's feedback score; neutral feedback does not affect the feedback score. When a member's feedback score is more than ten, a yellow star appears beside the member I.D. and different colored stars are associated with different ranges of the feedback scores. The member profile includes the number of members who left a positive feedback (NMPF); the number of members who left a negative feedback (NMNF); Feedback Score, which is the difference between NMPF and NMNF; Positive Feedback Percentage, which is NMPF over the sum of NMPF and NMNF; and the number of all positive feedback. The accumulative scores for positive, neutral and negative are listed for the past month, past six months and past twelve months, as are recent ratings for a member's profile. All the feedback ratings, feedback comments and the raters' profiles and the number of mutually withdrawn feedback are all visible to the public. Since May, 2007, eBay starts providing detailed seller ratings including criteria of "item as described", "communication", "shipping time", and "shipping and handling charges". Each of these detailed seller ratings is an average of the corresponding ratings by the buyers. Figure 2.2 is a snapshot of the profile of a member seller with eBay.

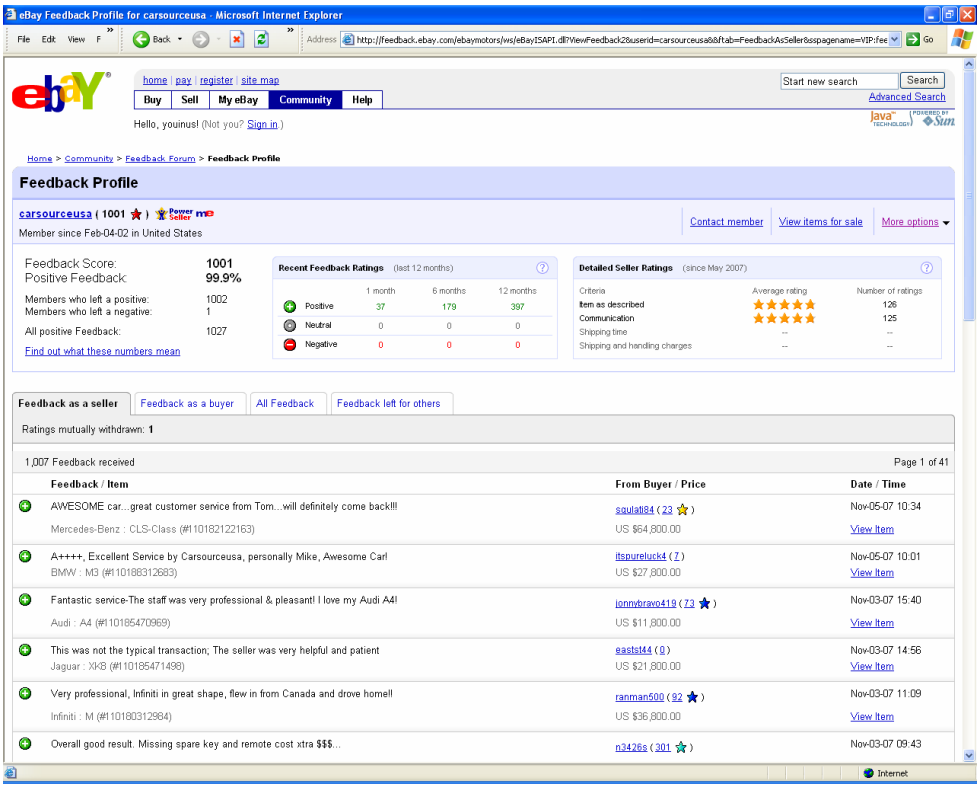

Figure 2.2 EBay Member Profile Adapted from eBay (eBay, 2007)

There are other reputation models similar to what Amazon.com and eBay.com use. The essential concept of these models is to take the average of all the ratings on an entity as its reputation value. We call this kind of reputation model the traditional reputation model.

2.1.2 Marsh's Model

Marsh's (P. S. Marsh, 1994) work is among the earliest in which trust is separated into three different aspects:

- *Basic Trust*, which is the overall trusting disposition of the evaluating agent itself, derived from its entire past experience;

- *General Trust*, which is the general trust on the evaluated agent without any situational hint; and
- *Situational Trust*, which depends on the situation and context in which the evaluated agent is evaluated and is of most importance in cooperative situations.

To determine the *situational trust*, *knowledge*, *utility* and *importance* factors are introduced in Marsh's model. The basic equation to calculate the *situational trust* is

$$T_x(y,\alpha)^t = U_x(\alpha)^t \times I_x(\alpha)^t \times E(T_x(y)^t),$$

where x is the evaluating agent, y is the evaluated agent, α is the situation, $U_x(\alpha)^t$ is the utility x gains from situation α, $I_x(\alpha)^t$ is the importance of the situation α, and $E(T_x(y)^t)$ is the estimation of the *basic trust* x on y at time t. *Knowledge* as a binary variable indicates whether the evaluating agent knows the evaluated one or not. *Utility*, as a real number within [-1, +1], is what a rational economic entity tries to maximize. *Importance*, as a real number within [0, +1], indicates how important a situation is for the evaluating agent. However, this solution produces some nonsensical behaviors of the agent; for example, negative *utility* and negative estimation of *basic trust* produce a positive value of *situational trust*. To determine whether the evaluating agent should cooperate with the evaluated, a cooperation threshold is suggested based on the *perceived risk*, *perceived competence,* and the estimate of the *general trust* and the *importance* of the situation as in the basic equation of

$$Cooperation\_Threshold_x(\alpha) = \frac{Perceived\_Risk_x(\alpha)}{Perceived\_Competence_x(y,\alpha) + E(T_x(y))} \times I_x(\alpha),$$

in which the perceived risk is not formalized and, again, this equation leads to some nonsensical behaviors. While evaluating the trust of an agent, this model only considers the experiences of the evaluating agent itself. It does not account for other agents' interactions and experiences with the evaluated agent.

2.1.3 Abdul-*Rahman and Hailes' Model*

Abdul-Rahman and Hailes (Abdul-Rahman & Hailes, 2000) suggest a trust model grounded in real-world social trust and based on a word-of-mouth mechanism. This paper categorizes trust into three types of trust:

- Interpersonal Trust which is context specific and depends on direct trust an agent has on another;
- Impersonal Trust (Shapiro, 1987; Zucker, 1986) which is based on third-party structures, also known as Institution-based Trust; and
- Dispositional Trust, which is the Basic Trust as in Marsh's trust model.

Actually only Interpersonal Trust is modeled using four trust degrees categories as vt (very trustworthy), t (trustworthy), u (untrustworthy) and vu (very untrustworthy). For each evaluated agent and context, in a Q set, the evaluating agent maintains a tuple holding the number of corresponding experience in each trust degree category. The direct trust of the evaluated will be the category with the largest number in the corresponding tuple. If there are any ties, an uncertain value is assigned to the direct trust, among "Mostly Good and Some Bad," "Mostly Bad and Some Good," and "Equal Amount of Good and Bad." Before combining the trust evaluation from the recommender agents, the evaluating agent adjusts each recommender agent "witness"

based on the difference between its evaluation and the recommender's evaluation. Each evaluating agent also maintains an R set holding the context information and the recommendation adjustment information tuple for each recommender agent. Based on the information in the R set, the evaluating agent calculates the weighted sum of the witnesses from the recommender agents. After each direct experience with an evaluated agent, the experience is used to update the Q set and R set, accordingly. The Basic Trust value is not used directly to compute the trust value of the evaluated agent; instead, it is used to calculate the semantic distance which is further used to adjust the witness from the recommender agent.

2.1.4 Sen and Sajja's Model

Sen and Sajja (Sen & Sajja, 2002) propose a reputation-based trust model which tackles the minimum number of witness agents an agent needs to query to solicit the witnesses' evaluation of an evaluated agent in order to meet a guaranteed good choice of provider (namely seller agent) in a noisy environment, where some agents consistently lie. The following inequality is used to calculate the minimum number of witness agents of q

$$\sum_{i=\max\left(\left\lceil \frac{q}{2} \right\rceil, \left\lfloor \frac{q}{2} \right\rfloor+1\right)}^{P} \frac{C_{N-1}^{i} \cdot C_{l}^{q-i}}{C_{N}^{q}} \geq g \ ,$$

where N is the population of buyer agents, P is the population of seller agents, l is the number of liars, which is smaller or equal to N/2; and g is the probabilistic guarantee threshold. The agents use reinforcement learning (Sutton & Barto, 1998) to learn the estimate of a provider's reputation by either direct interactions with the provider or by

observation of the interactions between other agents and the provider by the following equations of

$$e_{ij}^{t+1} = (1-\alpha_i)e_{ij}^{t} + \alpha_i r_t$$
$$e_{ij}^{t+1} = (1-\alpha_o)e_{ij}^{t} + \alpha_o r_t,$$

Where r_t is the performance of agent j, received or observed by evaluating agent i; α_i, α_o are interaction and observation learning rate, respectively; and the former is greater than the latter to realize the fact that direct interaction is more influential on the reputation estimation than the observed actions. But the evaluating agent's direct interaction, which is the most accurate input of the evaluated agent's reputation, is not integrated into the witnesses' evaluation of the evaluated to obtain the ultimate reputation value of the evaluated.

2.1.5 Huang's Model

Huang (Huang, 2004) proposes a model depicted in figure 2.2 to compute the trustworthiness of agents in a peer-to-peer electronic trading environment. In the model, the trust value of the evaluated agent is determined by the evaluating agent's memory, which is a benefit value of past transaction experienced with the evaluated agent; the testimony of the evaluating agent's neighborhood, which is an integrated memory value from the evaluating agent's neighbors who have prior trading experiences with the evaluated agent; and the trading environment situation the evaluating agent perceives while evaluating the trust of the evaluated. Memory span, memory fading and weighting schemes are conducted on the raw memory data to deduce the memory factor which is then used to compute the trust value. A fuzzy inference process is utilized to compute

the trust of the evaluated agent based on the input of corresponding memory and testimony.

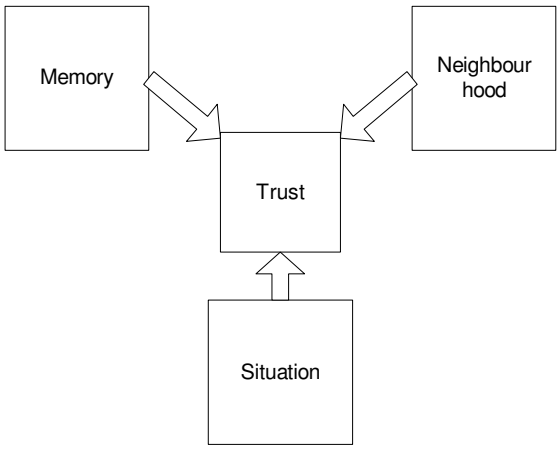

Figure 2.3 Trust Model of Huang (Huang, 2004)

But as stated in this paper, the detection of the agent's due environment situation is an open issue; the situation is an assumed set and understood by all agents. The testimony, which is implemented as the average of trust evaluations from the evaluating agent's neighbors, can also be improved by taking into consideration the reliability of the neighbors.

2.1.6 Huynh et al.'s FIRE Model

Huynh et al. (Huynh, Jennings & Shadbolt 2006) introduce an integrated trust and reputation model, FIRE, which adopts four sources of trust information to evaluate the trustworthiness of the seller agents. The four sources are

- direct experience, which is the evaluating agent's prior direct interaction experience with the evaluated, which further implies the Interaction Trust (IT);

- witness information, which is based on the collected experiences of other agents who have interacted with the evaluated agent, which implies the Witness Reputation (WR);
- role-based rules, which are some domain-specific norms or heuristic values that can help the evaluating agent to determine the trustworthiness of the evaluated, which implies the Role-based Trust (RT); and
- third-party references provided by the evaluated agents, which are like the references job hunters provides with their resumes, which implies the Certified Reputation (CR).

The IT component is calculated based on each rating-recency-function-weighted direct interaction experience of the evaluating agent with the evaluated one to make sure that older ratings weigh less.

Inspired by Yu and Singh's (Yu & Singh, 2002) referral system, an evaluating agent can query its acquaintances and the acquaintances of the acquaintances for witness testimony of the evaluated agents. With the assumption that an agent knows with which agent the testimony query about the evaluated can be fulfilled, with hand-picked branching factor (determines the number of acquaintance to query) and referral length factor (determines the depth of the referral chains), WR is calculated as the average of all the rating-recency-function-weighted testimonies.

There is no general method to computationally quantify role-based trust. Rules, given by the agent owner or designer, are used to assign RT values for the RT component. For example, if the seller agent is a government seller, the quality of the

transaction will be 0 among [-1, +1] interval with the influence level of 0.8. When there are conflict rules, the consistency of the values in this component will be low; the weight of this component will be less in the overall trust model.

With the requirement that each seller agent must keep the reference information issued by each buyer agent with whom there was prior direct interactions, an evaluating agent can ask the evaluated to provide the references. Based on the rating-recency-function-weighted references, the CT is calculated.

The overall trust value is the normalized weighted sum of the four trust components each with the corresponding end user hand-picked coefficients and deduced reliability. The trust equation for each trust component is

$$\mathrm{T}_K(a,b,c) = \frac{\sum_{r_i \in \Re_K(a,b,c)} \omega_K(r_i) \cdot \upsilon_i}{\sum_{r_i \in \Re_K(a,b,c)} \omega_K(r_i)},$$

where $\mathrm{T}_K(a,b,c)$ is the trust value agent a has in agent b in terms of c; K is one of the trust sources of IT, WR, RT and CR; $\Re_K(a,b,c)$ is the set of ratings from trust source of K; and $\omega_K(r_i)$ is the rating weight function to calculate the reliability of the rating r_i and υ_i is the value of rating r_i. The overall trust value is

$$\mathrm{T}\ (a,b,c) = \frac{\sum_{K \in \{I,R,W,C\}} \omega_K \cdot T_K(a,b,c)}{\sum_{K \in \{I,R,W,C\}} \omega_K},$$

where $\omega_K = W_K \cdot \rho_K(a,b,c)$, and W_I, W_R, W_W, W_C, which are set by end users or the designer, are the corresponding coefficients of IT, RT, WR and CR trust components. $\rho_K(a,b,c)$ is the reliability of a trust component and is calculated by

$$\rho_K(a,b,c) = \rho_{RK}(a,b,c) \cdot \rho_{DK}(a,b,c),$$

$$\rho_{RK}(a,b,c) = 1 - e^{-\Upsilon K \cdot \sum_{r_i \in \Re_K(a,b,c)} \omega_K(r_i)},$$

$$\rho_{DK}(a,b,c) = 1 - \tfrac{1}{2} \cdot \frac{\sum_{r_i \in \Re_K(a,b,c)} \omega_K(r_i) \cdot \left| \upsilon_i - T_K(a,b,c) \right|}{\sum_{r_i \in \Re_K(a,b,c)} \omega_K(r_i)},$$

where $\rho_{RK}(a,b,c)$ is the rating reliability; γK is the reliability-function-slope-adjustment parameter; $\rho_{DK}(a,b,c)$ is the deviation reliability.

Besides the overall trust value, its reliability is also provided as the product of the rating reliability and the deviation reliability as calculated in equations of

$$\rho_T(a,b,c) = \frac{\sum_{K \in \{I,R,W,C\}} \omega_K}{\sum_{K \in \{I,R,W,C\}} W_K}$$

This trust and reputation model is depicted in figure 2.4.

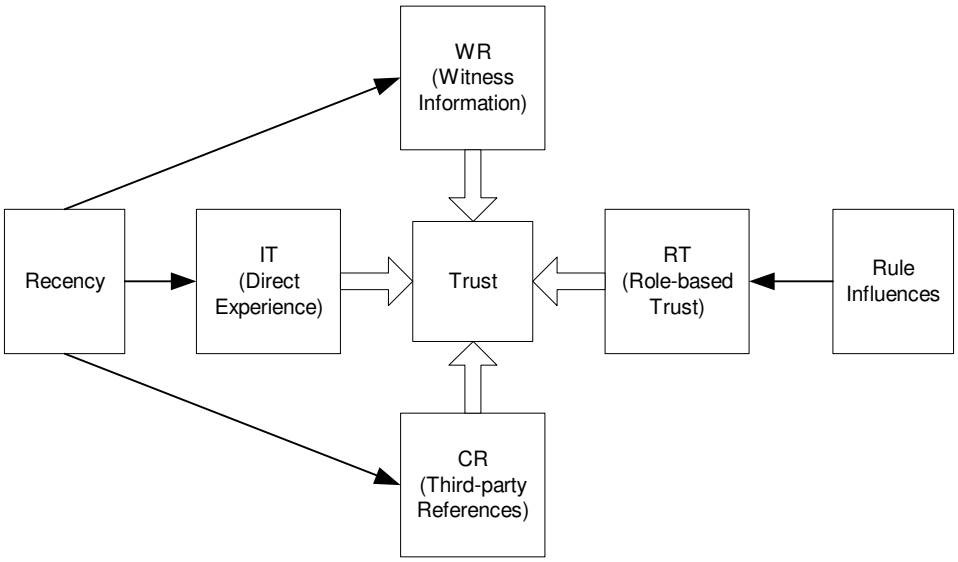

Figure 2.4 FIRE Trust Model (Huynh, Jennings & Shadbolt 2006)

2.2 Drawbacks of Extant Trust and Reputation Models

Most of the models are built based on intuitions which lack theoretical or empirical supports. As stated by Marsh (S. P. Marsh, 1994) "… we start with what are by and large intuitive ideas about how trust works, based on experience …."

Most of the trust or reputation models conceive the outcome of the agents' interactions as being binary; that is, the strategy of one agent is either cooperation or defection. Binary outcome of the agents' interactions simplify the coding of the testing system, but the findings may be biased which may not be realistic.

Most of the trust or reputation models make unrealistic assumptions which hinder their use in the real E-Marketplace. For instance, in Huynh's model, the agents are assumed to be honest in sharing information about their experiences with other agents and agents are willing to share their experiences. In reality, there is a moderate amount of noise in feedback posted and honesty in sharing experiences is not

guaranteed. As is indicated by a survey of eBay users, "… users hesitate to give negative feedback because of fear of retaliation from their transaction partners, … many users choose either to give positive feedback to a problematic transaction, or just not leave any feedback at all (Zacharia, 1999)." The users' behavior of choosing to give positive feedback to a problematic transaction is the same as that of a liar. The action of not leaving any feedback is the same as not sharing information about transaction experiences with others. Most of the trust or reputation models are not designed to deal with missing data, i.e., buyers' choosing not to provide any feedback. In addition, if there is no proper built-in mechanism, the sharing agents actually bear more burden to provide information for other agents than those who are not sharing. In this case, a rational agent would rather not share and choose the free-riding strategy.

Most of the traditional trust or reputation models can be explored by fraudulent sellers using shills to boost their reputation.

CHAPTER 3

PROPOSED ADAPTIVE REPUTATION-BASED TRUST MODEL

In this paper, the author takes the following stance that trust is the expectation that the service will be provided as promised in the coming events and that reputation is what Mui et al. (L. Mui & Halberstadt, 2002) define as perception that an agent creates through past action about its intentions and norms. In the proposed adaptive reputation-based trust model, two information sources of reputation are utilized to estimate the trust value: the ratings of direct interactions between the evaluating agent and the evaluated one and other agents' ratings of the evaluated agent about their direct interactions. The former is termed as Direct Reputation, the same concept as the term of "image" defined by Conte et al. (Conte & Paolucci, 2002); the latter is termed Witness Reputation. According to Mui et al.'s typology (Mui, Halberstadt & Mohtashemi, 2002), the two information sources are encounter-derived reputation and observed reputation, respectively. These two are the most commonly used information sources for trust/reputation model computation.

Based on the reputation information, the evaluating agent can estimate the trust in the evaluated agent. If the trust of the evaluated agent is desirable, it may lead to actual purchase. In the model, the path from trust to purchase is dash-lined, which means trust between the two business partners may not necessarily lead to a business transaction. There are other factors in cooperation with trust which lead to a business

transaction. The relationship between trust and purchase is not modeled in this research; however, this research needs the evaluating agent's evaluation (rating) of the transaction to enhance the accuracy of the trust estimation and to enable the learning of the parameters of the reputation-based trust model. The research assumes the evaluating agent can properly evaluate the transaction. The evaluation of a purchase is the feedback to update the reputation and trust values.

The diagram of the proposed adaptive reputation-based trust model is depicted in figure 3.1.

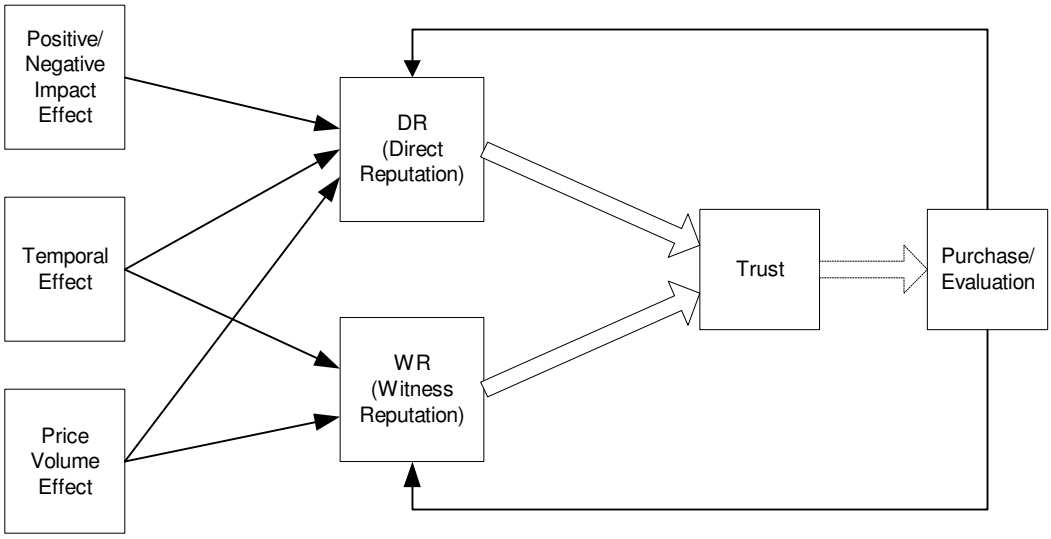

Figure 3.1 The Proposed Adaptive Reputation-based Trust Model

In this paper the following notations are used, as listed in table 3.1.

Table 3.1 Notations in the Proposed Reputation-based Trust Model

Notation	Description	Domain
a_1, a_2, …	Agent's ID	
A	Agent Sets	
$T_{a_m a_n}(t)$	Agent a_m's overall estimated trust value in agent a_n based on the information available at time t	[-1, 1]
$D_{a_m a_n}(t)$	Agent a_m 's Estimated Direct Reputation value (DR) in agent a_n based on the data of the direct transactions between them by time t. To estimate this value, the temporal factor, the positive and negative evaluation impact on the evaluating agent, and price and volume of the transactions involved are considered.	[-1, 1]
$W_{a_m a_n}(t)$	Agent a_m's Estimated Witness Reputation value (WR) in agent a_n based on the testimonies of other agents who have conducted direct transactions with agent a_n by the time of t.	[-1, 1]
$\rho_D(t)$	Reliability of component $D_{a_m a_n}(t)$	[0,1]
$\rho_{D_{cn}}(t)$	Reliability of component $D_{a_m a_n}(t)$ based on count of direct transactions between the two agents	[0,1]
$\rho_{D_{dv}}(t)$	Reliability of component $D_{a_m a_n}(t)$ based on the standard deviation of all the direct transactions between the two agents	
$\rho_W(t)$	Reliability of component $W_{a_m a_n}(t)$ by time t. It is the Product of the following three items.	[0,1]

Table 3.1-continued

$\rho_{W_{tc}}(t)$	Reliability of component $W_{a_m a_n}(t)$ by time t, based on the consideration of number of testimonies.	
$\rho_{W_{wc}}(t)$	Reliability of component $W_{a_m a_n}(t)$ by time t, based on the consideration of number of witnesses	
$\rho_{W_{dv}}(t)$	Reliability of component $W_{a_m a_n}(t)$ by time t, based on the consideration of the deviation of witness testimonies	
$\alpha_D(t)$	Weight for component $D_{a_m a_n}(t)$ at time t. This is a learnt parameter.	
$\alpha_W(t)$	Weight for component $W_{a_m a_n}(t)$ at time t. This is a learnt parameter.	
$r_{a_m a_n}(t)$	Agent a_m's rating on agent a_n, based on the direct transaction between them at time t	[-1,1]
$dD_{a_m a_n}(t)$	Direct Reputation Difference, i.e., if a_m selects a_n after estimating its trustworthiness, finishes the transaction and rates the transaction, the difference between the estimated direct trust value, if any, and the latest rating of the transaction .	
$dW_{a_m a_n}(t)$	Witness Reputation Difference, i.e., if agent a_z, other than a_m, has direct interaction with a_n at time t, the difference between a_z 's rating on a_n, $r_{a_z a_n}(t)$ and a_m 's Estimated Witness Reputation value on a_n, $W_{a_m a_n}(t)$	
$w_{tm}(t)$	Weight of each rating based on the time the rating is given	[0,1]

Table 3.1-continued

$w_{pn}(t)$	Weight of each rating based on the different impact on the evaluator of positive evaluation and positive evaluation	[0,1]
$w_{pv}(t)$	Weight of each rating based on the price and volume of the rated transaction	[0,1]
η_D	The learning rate for the weight of Estimated Direct Reputation	[0,1]
η_W	The learning rate for the weight of Estimated Witness Reputation	[0,1]
β_p	The weight for positive ratings	[0,1]
β_n	The weight for negative ratings	[0,1]
c_{tm}	The ad hoc constant for computing $w_{tm}(t)$	
c_{cn}	The ad hoc constant for computing $\rho_{D_{cn}}(t)$	
c_{pv}	The ad hoc constant for computing $w_{pv}(t)$.	
c_{tc}	The ad hoc constant for computing $\rho_{W_{tc}}(t)$.	
c_{wc}	The ad hoc constant for computing $\rho_{W_{wc}}(t)$.	
$countDR(r_{a_m a_n})$	The function returns the number of ratings used to compute the DR component.	
$countTC(r_{a_z a_n})$	The function returns the count of testimonies for WR calculation.	

Table 3.1-continued

$countWC(r_{a_z a_n})$	The function returns the count of witnesses for WR calculation.	
thresholdRepu	Threshold for S1Sellers and S2Sellers to start abusing reputation	
cpLSV	Listed Service Value for inexpensive items	
exLSV	Listed Service Value for expensive items	
m	Profit margin	
g	Positive real number, which is smaller than m. It determines the mean of actual service values of the sellers,	

3.1 Modeling Direct Reputation

The Direct Reputation (DR) is the estimated reputation value of the evaluated agent based on the evaluating agent's ratings of the direct transactions between the evaluating agent and the evaluated one. In order to estimate the DR, three factors of the ratings are considered which are the temporal-effect factor, the positive-negative-impact factor, and the price-volume factor.

3.1.1 Temporal-effect Factor of the Ratings

Old ratings carry less weight than new ones. A few models take the temporal factor into consideration. The REGRET reputation model (Sabater & Sierra, 2001) gives more relevance to recent ratings using a time dependent function, which gives more weight to recent ratings. In Huang's reputation model (Huang, 2004), five weight

functions are discussed depending on the degree of friendliness of the environment, which are equally-weighted, reverse-negative-exponential, triangular, negative-exponential, and most-recent functions. In Huynh et al.'s trust model (Huynh, Jennings & Shadbolt, 2006) a negative exponential function is introduced to realize the temporal effect of the ratings. Bolton et al.'s (Bolton, Katok & Ockenfels, 2004) empirical findings also provide insight into the use of this factor, as is stated "… buyers put more weight on recent feedback than old." In the proposed model, a negative exponential function is adopted to calculate the temporal-effect factor weights for the ratings as follows:

$$w_{tm}(t) = 1 - e^{-c_{tm} \cdot (t_i - t_0)}$$

where c_{tm} is a constant selected to control the slope the exponential curve and t_i-t_0 is the time difference between the rating time t_i and the starting time t_0 , which is set by the evaluating agent set.

3.1.2 Positive-Negative-Impact Factor of the Ratings

Taking a conservative stance, reputation should be easily ruined and hard to build. Reputation is usually acquired gradually over time and it can be destroyed very quickly (Dasgupta, 1988). When an agent is negatively rated, its reputation should drop dramatically. This solution can avoid abusing a high reputation rate for a long time. Yu and Singh (Yu & Singh, 2000) take similar conservative means in dealing with the negative ratings. In the suggested model, negative ratings are weighted more than the positive ratings in the estimate of the DR. It deserves further work to determine the precise weighting for positive and negative ratings. A weighting function can be

devised to fulfill the tasks. In order to probe the effectiveness of this factor in this paper, a subjective weight scheme is adopted, i.e. the weight for positive ratings is β_p and the weight for negative ratings is β_n, i.e.

$$w_{pn} = \begin{cases} \beta_p, if & r_{a_m a_n}(t) > 0 \\ \beta_n, if & r_{a_m a_n}(t) < 0 \end{cases}$$
$$0 < \beta_n, \beta_p < 1,$$
$$\beta_n > \beta_p.$$

3.1.3 Price-volume Factor of the Ratings

There are strategic sellers who build up their reputation and then start to cheat. It is highly likely that some sellers may abuse the feedback mechanism by selling cheap items to build up their reputation and then start to cheat on much more expensive items. There have been such instances reported with sellers on eBay. In order to discourage this kind of behavior, in the proposed model the price-volume factor of the ratings is also considered. The ratings for expensive items are weighted more than the less expensive items.

A negative exponential function similar with the one to calculate the temporal-effect factor weight is adopted to compute the price-volume factor weights as follows:

$$w_{pv}(t) = 1 - e^{-c_{pv} \cdot (price \cdot volume)}$$

where c_{pv} is a constant selected to control the slope the exponential curve and $price \cdot volume$ is the product of the price and the volume of the corresponding transaction that is rated by the rating.

3.1.4 The Direct Reputation Component

Combining the results of the above mentioned three weighting schemes constitutes the Direct Reputation component of the trust model. The results from different weighting schemes may affect the Direct Reputation differently and they can be further weighted to more precisely produce the Direct Reputation Component, which can be a topic for future research. Currently, for simplicity, the average of the three results is taken to compute the Direct Reputation Component as follows:

$$D_{a_m a_n}(t) = \tfrac{1}{3} \cdot [\frac{\sum_{i=0}^{t} r_{a_m a_n}(i) \cdot w_{tm}(i)}{\sum_{i=0}^{t} w_{tm}(i)} + \frac{\sum_{i=0}^{t} r_{a_m a_n}(i) \cdot w_{pn}(i)}{\sum_{i=0}^{t} w_{pn}(i)} + \frac{\sum_{i=0}^{t} r_{a_m a_n}(i) \cdot w_{pv}(i)}{\sum_{i=0}^{t} w_{pv}(i)}]$$

3.1.5 The Reliability of the Direct Reputation Component

In order to measure the reliability of the DR, two factors are taken into account; the number of ratings used to compute the DR and the concept of standard deviation of these ratings while taking the DR as the mean. The product of the two reliability measures is the reliability of the DR, i.e.

$$\rho_D(t) = \rho_{D_{cn}}(t) \cdot \rho_{D_{dv}}(t)$$

where $\rho_{D_{cn}}(t)$ is the reliability measure on the count of the ratings and $\rho_{D_{dv}}(t)$ is the reliability measure on the concept of standard deviation of the DR, respectively.

3.1.5.1 The Reliability on the Count of the Rating

The more ratings are involved in the computation of DR, the more reliable the DR is. Based on this observation, the reliability on the count of the ratings is formulated as:

$$\rho_{D_{cn}}(t) = 1 - e^{-c_{cn} \cdot countDR(r_{a_m a_n})}$$

where the $countDR(r_{a_m a_n})$ is the number of ratings used to compute the DR component.

3.1.5.2 The Reliability on the Concept of Standard Deviation of the DR

The fluctuation of the ratings around the DR is also an indicator of the reliability of the DR. If the ratings are steady with the same agent, the reliability of the DR should be higher than if the ratings fluctuate a lot. Based on this observation, the reliability on the concept of Standard Deviation of the DR is formulated as:

$$\rho_{D_{dv}}(t) = \frac{1}{1 + \sqrt{\dfrac{\sum_{i=0}^{t} (r'_{a_m a_n}(i) - D_{a_m a_n}(t))^2}{countDR(r_{a_m a_n}) - 1}}},$$

$$r'_{a_m a_n} = \tfrac{1}{3}[r_{a_m a_n}(i) \cdot w_{tm}(i) + r_{a_m a_n}(i) \cdot w_{pn}(i) + r_{a_m a_n}(i) \cdot w_{pv}(i)]$$

where the $countDR(r_{a_m a_n})$ is the number of ratings used to compute the DR component.

3.2 Modeling Witness Reputation

The Witness Reputation (WR) is the estimated reputation value of the evaluated agent based on the testimonies of other agents who have conducted direct transactions with the evaluated agent by the time of estimation. Other agents' ratings on an evaluated agent are the testimonies the evaluating agent uses to estimate the WR of the evaluated agent. Similarly, the temporal-effect factor and the price-volume factor of the ratings from the testimonies are considered to estimate the WR. The reason the positive-negative-impact factor is dropped here is that the positive-negative impact factor is subjective in nature. This factor can be viewed as the belief of an agent. If this factor is taken into account, there is a danger of falling into the complexity of modeling the belief of the belief. This paper does not intend to model the belief of belief; the focus of this paper is on the modeling of trust. To this end in this research the agent is retained as a first-order intentional system; that is, agents have beliefs and desires, but no beliefs and desires about beliefs and desires (Dennett, 1987)

3.2.1 Temporal-effect Factor and Price-volume Factor of the Ratings

Like the DR approach, the same equations are used to calculate the temporal-effect factor weights and the price-volume factor weights for the testimony ratings. The average of results from the two weighting schemes is used to calculate the witness reputation value from each witness as follows:

$$D'_{a_z a_n}(t) = \tfrac{1}{2} \cdot \left[\frac{\sum_{i=0}^{t} r_{a_z a_n}(i) \cdot w_{tm}(i)}{\sum_{i=0}^{t} w_{tm}(i)} + \frac{\sum_{i=0}^{t} r_{a_z a_n}(i) \cdot w_{pv}(i)}{\sum_{i=0}^{t} w_{pv}(i)} \right]$$

The sum of witness reputation values from all available witnesses constitutes the WR component of the trust model, i.e.,

$$W_{a_m a_n}(t) = \frac{\sum_{a_z \in A} D'_{a_z a_n}(t)}{countWC(r_{a_z a_n})}$$

where $a_z \in A, a_z \neq a_m, a_z \neq a_n$ and the function of $countWC(r_{a_z a_n})$ returns the count of witnesses.

3.2.2 The Reliability of the Witness Reputation Component

The reliability of the WR component accounts for three factors: the number of testimonies, the number of witnesses and the concept of standard deviation of the testimonies while taking the WR as the mean. The product of the three reliability measures is the reliability of the WR component, i.e.,

$$\rho_W(t) = \rho_{W_{tc}}(t) \cdot \rho_{W_{wc}}(t) \cdot \rho_{W_{dv}}(t),$$

where $\rho_{W_{tc}}(t)$ is the reliability measure on the count of the testimonies, $\rho_{W_{wc}}(t)$ is the reliability measure on the count of the witnesses and $\rho_{W_{dv}}(t)$ is the reliability measure on the standard deviation of the WR, respectively.

3.2.2.1 The Reliability on the Count of the Testimonies and the Witnesses

There are two observations. The greater number of testimonies that are used to compute the WR, the more reliable the WR is. But the testimonies from the same witness are less reliable than the same number of testimonies from different witnesses.

So in the model, the measures for the reliability on the count of the testimonies and on the count of the witnesses are differentiated as follows:

$$\rho_{W_{tc}}(t) = 1 - e^{-c_{tc} \cdot countTC(r_{a_z a_n})},$$

and

$$\rho_{W_{wc}}(t) = 1 - e^{-c_{wc} \cdot countWC(r_{a_z a_n})}$$

where $a_z \in A, a_z \neq a_m, a_z \neq a_n$, and c_{tc}, c_{wc} are constants to control the slope of the corresponding exponential curves and the function of $countTC(r_{a_z a_n})$ returns the count of testimonies and $countWC(r_{a_z a_n})$ returns the count of witnesses for WR calculation.

3.2.2.2 The Reliability on the Concept of Standard Deviation of WR

Similarly, if the witness testimonies on one evaluated agent deviate more, its WR is less likely to be reliable. In the proposed model, the standard deviation concept is adopted to reflect this concern as follows:

$$\rho_{W_{dv}}(t) = \frac{1}{1 + \sqrt{\dfrac{\sum_{a_z \in A} (D'_{a_z a_n}(t) - W_{a_m a_n}(t))^2}{countWC(r_{a_z a_n}) - 1}}},$$

where $a_z \in A, a_z \neq a_m, a_z \neq a_n$.

3.3 Combining the Direct Reputation and the Witness Reputation

The E-Marketplace environment determines the corresponding weights of DR and WR in the proposed trust model. The DR usually is more reliable than the WR since the DR is based on the evaluating agent's direct and personal transaction with the

evaluated agent. In an environment where all agents share information and tell the truth, the WR should be very reliable, too. In this case, the WR can be the most efficient means for the evaluating agent to estimate an unknown transaction partner since the evaluating agent can receive the correct reputation estimate on the evaluated agent based on the WR without having corresponding direct transactions with the evaluated agent. But in an environment where some agents lie about testimonies or some agents are not willing to share bad experiences, the WR will be less reliable. Also the E-Marketplace is open, i.e. buyers and sellers are free to enter and exit the E-Marketplace. This adds more uncertainty and dynamics in the environment. In the proposed adaptive reputation-based trust model, the agents use reinforcement learning to adjust the weights for the components of DR and WR components so as to be able to estimate others' reputation more accurately and adaptively.

3.3.1 Learning of the Weights of the Components of DR and WR

The values of the DR and WR are adjusted incrementally, as well as their corresponding weights while transactions are occurring in the E-Marketplace.

3.3.1.1 Direct Reputation Difference and the Weight of the DR

The Direct Reputation Difference is computed after each direct transaction between the evaluating agent and the evaluated one. For instance, at time t, if a_m selects a_n after estimating its reputation-based trust ($T_{a_m a_n}(t)$ based on the reputations of $D_{a_m a_n}(t)$ and $W_{a_m a_n}(t)$) by the proposed model and conducts the transaction and then at the end of time t rates the service of a_n as $r_{a_m a_n}(t)$ in the transaction, the difference

between the estimated Trust value, $T_{a_m a_n}(t)$, if any, and the latest rating of the transaction, $r_{a_m a_n}(t)$ is the Direct Reputation Difference at time t. The Direct Reputation Difference equation is:

$$dD_{a_m a_n}(t) = r_{a_m a_n}(t) \ - T_{a_m a_n}(t) .$$

This difference then is used by the evaluating agent to learn the weight of the DR by the following equation:

$$\alpha_D(t+1) = \alpha_D(t) + \eta_D \cdot dD_{a_m a_n}(t) ,$$

where $\alpha_D(t+1)$ is the weight of the DR component in trust estimation computation for next transaction and η_D is the learning rate.

3.3.1.2 Witness Reputation Difference and the Weight of the WR

Similarly, Witness Reputation Difference and the weight of the WR are calculated when there is testimony from any other agent from the E-Marketplace. Witness Reputation Difference is the difference between the average of a_z's ratings on a_n, $r_{a_z a_n}(t)$ and a_m's Trust value on a_n at time t, $W_{a_m a_n}(t)$, when other agent, for instance, agent a_z , other than a_m , has direct transaction with a_n at time t. The following equation is used to calculate Witness Reputation Difference:

$$dW_{a_m a_n}(t) \ = \overline{r_{a_z a_n}(t)} - T_{a_m a_n}(t) .$$

This Witness Reputation Difference then is used by the evaluating agent a_m to learn the weight of the WR by the following equation:

$$\alpha_W(t+1) = \alpha_W(t) + \eta_W \cdot dW_{a_m a_n}(t) .$$

Then at the end of time t, the WR value is updated using the updated weight of the WR and the testimony of $r_{a_z a_n}(t)$.

3.3.2 The Reputation-based Trust Model

Up to now, all the needed components of reputation with their corresponding weights and reliability measures are available. The Reputation-Based Trust model is formulated as:

$$T_{a_m a_n}(t) = \frac{\alpha_D(t) \cdot \rho_D(t) \cdot D_{a_m a_n}(t) + \alpha_W(t) \cdot \rho_W(t) \cdot W_{a_m a_n}(t)}{\alpha_D(t) + \alpha_W(t)} .$$

CHAPTER 4

METHODOLOGY

Multi-Agent System simulation is the method used to compare the effectiveness and robustness of the proposed model with that of the competing trust and/or reputation models. The agent simulation package of Repast J is used to build the multi-agent system to simulate the interactions among the buyers and seller in a mini E-Marketplace.

4.1 The Relevance of Simulation Methods

The simulation methods are valid research methodologies and are gaining ever greater attention from researchers. By using simulation methods, researchers have discovered significant research findings. The Garbage Can Model of Organizational Choice is developed by using simulation methods (Cohen, March, & Olsen, 1972). "Simulation is particularly effective when the theoretical focus is longitudinal, non-linear, or processual, or when empirical data are challenging to obtain" (Davis, Binghan & Eisenhardt, 2007). In the real settings of this research, a real E-Marketplace, trust and reputation take a long time to build up. In this research, the model of trust and reputation is non-linear. Empirical data are difficult to obtain especially for a hybrid E-Marketplace with human agents and intelligent agents or for an E-Marketplace with only intelligent agents. The choice of simulation methods for this research is sound and prudent.

As to the choice of using MAS simulation, the essential idea that is taken is "… many phenomena, even very complex ones, can best be understood as systems of autonomous agents that are relatively simple and follow relatively simple rules for interaction" (Samuelson & Macal, 2006). The emerging agent-oriented E-Marketplace subsumes the complex characteristics and consists of systems of autonomous agents that are relatively simple and follow relatively simple rules for interaction. Researchers are sure to use MAS to study the phenomena of intelligent agents in the emerging agent-oriented E-Marketplace as is done in this paper. Even for the hybrid E-Marketplace where human agents and intelligent agents coexist, MAS is still a good choice to conduct the corresponding research. Nissen and Sengupta (Nissen & Sengupta, 2006) reveal the emerging use of intelligent agents in enterprise supply chain. In their research, an Intelligent Mall, where human agents and intelligent agents can interact with each other, is set up to test the hypotheses about performance comparisons of human agents and intelligent agents under different task circumstances in maintenance, repairs, and operations (MRO) procurement. In this research, a mathematical equation of the trust is proposed, but its effectiveness and robustness are unknown. MAS is to be set up so as to collect corresponding data and visual output to demonstrate the modeling (Axtell, 2000) and also allow for model comparison with competing models. The choice of MAS simulation method for this research is sound and prudent.

Even though the empirical data are difficult to obtain for this research, some field data can still provide insights into this research. There are human agents who are

players in the current E-Marketplace. The human agents share a lot of common relevant characteristics with the intelligent agents as mentioned in previous chapters. They do not meet each other face to face, there are no personal hues beyond the historical feedback and ratings, online consumers are goal-oriented. The model proposed by this research can be cross-validated by field data from current E-Marketplaces such as eBay and Amazon.

4.2 System Design

The system is composed of seller agents (sellers), buyer agents (buyers), a Bulletin Board (BB) and a calculator. On the BB, sellers can post the information about items for sale and buyers can post their feedback of the transactions with sellers. The calculator reads the BB and preprocesses the reputation data for the rest agents.

In order to simulate the missing data and noisy data on the feedback ratings in a real E-Marketplace, variables of Feedback Posting Rate (FPR) level and noise level are devised into the system. The former controls the percentage of buyers who give feedback and the latter controls the level of noise added to the feedback ratings.

An informal sensitivity analysis is done so as to pick up the values of the parameters of the simulation. The values of the parameters used in the simulation are listed in appendix D.

4.2.1 Seller Agents

There are five kinds of sellers in the mini E-Marketplace. They are 1GSellers (1GS), 0.8GSellers (0.8GS), 0.5GSellers (0.5GS) and two kinds of strategic sellers of Strategic-Type-One sellers (S1S) and Strategic-Type-Two sellers (S2S). The sellers

provide either satisfactory service or unsatisfactory one. The actual service values (ASVs) of the satisfactory service are drawn from distinct normal distributions with the corresponding designated service means. So are the ASVs of the unsatisfactory service but with different designated service means. The designated service mean of the satisfactory service is greater than a Listed Service Value (LSV) and that of the unsatisfactory service is less than the LSV. The 1GS sellers always provide satisfactory service. 0.8GS and 0.5GS sellers provide satisfactory service with the probability of 80% and 50%, respectively; for the rest of the time, they provide unsatisfactory service. An S1Seller calculates its own reputation based on the traditional model to determine whether it should provide satisfactory service or not. If an S1Seller's self-estimated reputation value is lower than a threshold value (thresholdRepu), the S1Seller provides satisfactory service; otherwise, unsatisfactory service. An S2Seller behaves exactly as what an S1Seller does, besides using shills to gain undeserved reputation.

In the system design, in regards of trust per sé, 1GSellers are the most trustworthy and 0.5GSellers or S2Sellers are among the most untrustworthy since S2Sellers not only abuse the reputation but also use shills to gain undesired reputation. The trust values of the S1Seller, 0.8GSeller and 0.5GSeller fall between that of the 1GSeller and the S2Seller.

We assume there are no capacity constrains. This is all sellers have unlimited number of goods to meet the demands of buyers. There can be two LSVs, one for high-priced goods, the other for low-priced goods. The simulation is to test the proposed model in two item situations. One is the one-item situation where there is only one type

of goods; the other is the two-item situation where there are expensive and inexpensive goods in the E-Marketplace.

4.2.2 Buyer Agents

In this simulation experiment, in a run, all buyers are equipped with a same trust model from the tradition model, Huynh's model and the proposed model. In each time period (henceforth referred to as a tick), a buyer generates its demand based on normal distribution and then selects seller(s) to do business with. In one-item situation, the buyers always purchase all the demand from one seller. But in two-item situation, a buyer may choose a different seller to purchase the two types of goods. At the time a buyer selects a seller, the buyer calculates all the sellers' trust values and then uses Boltzmann distribution (Kaelbling & Littman, 1996) to determine with which seller to conduct the transaction. Boltzmann's algorithm allows a buyer to both exploit its knowledge about the sellers' trust and explore potential good sellers. After a transaction, the buyer calculates the ratings of the transaction and then the buyer may choose posting the feedback which is determined by the buyer's attribute of Post Feedback. To simulatet the The attribute of Post Feedback of each buyer is globally set based on the FPR level when the system is initialized at the very beginning. If the attribute of Post Feedback of a buyer is on, the buy always posts feedback honestly; otherwise, the buyer does not post feedback on any transactions. The buyers are assumed to be honest in payment, i.e. they always pay the corresponding sellers for the LSV to close the corresponding transactions.

4.2.3 Bulletin Board

This is the virtual place where sellers can post their items on sale and buyers can post their feedback about transactions. All the data of a posted item are posted on the BB, including the item name and the LSV. All the data of each closed transaction are posted as feedback on the BB, including buyer's I.D., seller's I.D., item name, transaction volume, LSV of the transaction, ASV of the transaction, and timestamp. The BB keeps the data of both feedback and posted items.

4.2.4 Calculator

The calculator is designed as a special agent, which reads about the posted transaction data and preprocesses the corresponding data so as to be used by the buyers to determine the trust values of the sellers. The calculator can reduce the computation complexity in the trust computation of the buyers.

4.2.5 Length of Updating Trust and Reputation Value

Dellarocas (Dellarocas, 2006) indicates that in the pure moral hazard settings, if ratings are noisy and the per-period profit margin of cooperating sellers is sufficiently high, a mechanism of not publishing every single rating when it is available but rather, waiting till the ratings of k transactions are available and publishing a summary statistics of a trader's most recent k ratings can induce more average levels of cooperation and market efficiency than a mechanism of publishing the overall ratings as soon as they are available. But the optimal discount factor of past ratings is still an open question. And it goes without saying that even the per-period profit margin of cooperating sellers is not sufficiently high. If the ratings are updated whenever a rating

is available after a transaction, the whole system will be too busy to handle matters other than updating the ratings. But, as to our system, the mini E-Marketplace has a limited number of buyers and sellers. To update the trust or reputation value is not that costly. In our system, the ratings are updated every transaction.

4.2.6 Propagated Reputation

The Propagated Reputation is the reputation information passed from through a chain of agents. The propagated reputation can be implemented using Mui's Bayesian algorithm model (Lik Mui, Mojdeh, Cheewee & Peter, 2001). In 2001, Mui et al. did simulations to study the conditions under which Tit-For-Tat (TFT) agents are evolutionarily stable when they use different notions of reputation to evaluate agents with whom to interact (Mui, Halberstadt & Mohtashemi, 2002). These TFT agents after enhanced by the designated reputation, become Reputation-enhanced TFT agents (RTFT). In their study, among four reputation schemes of Encounter-derived Individual Reputation (EIR), Observed Individual Reputation (OIR), Group-derived Reputation (GR) and Propagated Reputation (PR), the PR scheme and the GR scheme lead to the threshold with the least number of encounters per generation (EPG) to become stable, which is far less than the EPG for EIR and OIR. This is a clear indication that the use of the GR and PR schemes can be much more efficient and effective to evaluate the reputation of an agent in a community, if the communication cost is ignored. Either GR or PR or both should be included in the trust model. Of course, the GR and PR are built upon the individual agent's EIR. As in our system, no propagated reputation is used since all the feedback data of each transaction are available via the BB.

4.2.7 Defection of Cooperation, Binary or Continuous

Most of the simulations validating the trust models treat the outcome of the agents' interactions as being binary; that is, either cooperation or defection. To be more realistic, this research adopts a continuous outcome of the agents' interaction, that is, agents can cooperate partly or defect partly. A seller's ASV is a continuous variable which fluctuates around certain designated means and follows a certain normal distribution.

4.3 Simulation Experiment Plans

There are two 2×2 experiments in the simulations. The first 2×2 experiment involves factors of number of items, and noise level; and the second involves factors of number of items and FPR level. In combination with three noise levels on the ratings with the mean of zero and standard deviations of 0, 0.2 and 0.5, respectively, and three FPR levels (100%, 80%, 50%), the performance of the full model of the proposed adaptive reputation-based trust model (hereafter, called proposed model) is compared with the traditional reputation model (hereafter, called traditional model) and the weighted combination of Direct Trust and Witness Reputation of Huynh's trust model (hereafter called Huynh's model), respectively.

Buyers' tick gain and sellers' tick gain are used to measure the performance of the buyers and sellers with different models at different noise levels and FPR levels, respectively.

4.3.1 Model Comparison Plans

There are total of thirty simulation plans, each simulation plan is a combination of a trust model and a scenario. One scenario is a combination of number of items and one noise level or one FPR level. The scenarios with noise level of zero and FPR level of 100% are the base scenarios, so there are two base scenarios for each model and in total, there are ten different scenarios. For each scenario, ten runs are conducted; in each run the corresponding seed set for the needed random numbers in an experiment is utilized and each run stops at the thousandth tick.

4.3.1.1 Performance Measure of the Buyers

In the mini E-Marketplace, when a seller intends to sell some item, it posts a LSV and hides the corresponding ASV until after the transaction is completed. In the simulation, the LSV of a cheap item is cpLSV, and that of an expensive item is exLSV. Depending on the difference between the LSV and ASV, buyers' ratings on a seller range from -1 to +1. The equation of the feedback ratings is:

$$-1 \le r_{a_m a_n}(t) = \frac{ASV - LSV}{3\sigma + g \cdot LSV} \le 1,$$

namely,

$$(1-g) \cdot LSV - 3\sigma \le ASV \le (1+g) \cdot LSV + 3\sigma,$$

where σ is the standard deviation of the normal distribution of the ASV.

The buyer a_m's gain (GB) from the transaction with seller a_n is defined as:

$$GB_{a_m a_n}(t) = ASV - LSV.$$

In each run, the total-tick-gains of all buyers in each tick are collected and only the last 100 total-tick-gains are averaged to represent the Overall Tick Gain (OTG) of the buyers in that run. The average of the overall tick gains of the buyers in ten runs represents the Comparable Tick Gain (CTG) of the buyers in one scenario. By comparing the CTGs of the buyers within a model with different noise levels and FPR level and across different models, we compare the proposed model with the competing models from the point of view of the buyers.

4.3.1.2 Performance Measure of the Sellers

In the simulation, the performances of different seller groups are also compared. The profit margin (m) for all sellers is set to be the same. The gross profit of a seller is defined as m*LSV, which is then used to calculate the gain of a seller. Depending on the predetermined behavior and standard deviation of the ASV (SDASV), a seller's ASV varies around the designated mean of the actual service value (MASV) of its status. The MASV of the satisfactory service is set to be (1+g)*LSV, and that of the unsatisfactory service is set to be (1-g)*LSV, where g is a positive value smaller than m. The ASVs of satisfactory and unsatisfactory service share the same SDASV of σ. A seller a_n's gain (GS) from the transaction with buyer a_m is defined as:

$$GS_{a_m a_n}(t) = (LSV - ASV) + m \cdot LSV .$$

The following inequalities should hold to guarantee that the sellers always make some positive gain and that ASVs of satisfactory service never fall below the LSV and the ASVs of unsatisfactory service never go above the LSV:

$$GS_{a_m a_n}(t) = (LSV - ASV) + m \cdot LSV > 0,$$

$$\sigma < \frac{(m-g) \cdot LSV}{2},$$

$$m > g.$$

The ASVs of satisfactory service are in the range of $[(1+g) \cdot LSV - 2\sigma, (1+g) \cdot LSV + 2\sigma]$; the ASVs of unsatisfactory service are in the range of $[(1-g) \cdot LSV - 2\sigma, (1-g) \cdot LSV + 2\sigma]$. Since a buyer's rating on a seller is in the range of [-1, +1], so $\sigma \leq \frac{(1-g) \cdot LSV}{2}$. All proofs are in the appendix A.

Similar to the performance measure of the buyers, the total-tick-gains of all sellers of the same kind in each tick are collected. The last 100 total-tick-gains are averaged to represent the OTG of the sellers of the same kind in a run. The average of the OTGs of the sellers of the same kind in ten runs represents the CTG of the sellers of the same kind in one scenario. By comparing the CTG of the different seller groups, one can judge the performance of difference sellers group within a model and across different models at different noise levels and FPR levels.

4.3.2 Two Different Item Situations

In the real settings of an E-Marketplace, it is very common for a seller to trade on items in the same category but at dramatically different price levels. For example, on-line auto dealers may sell new cars and trade-ins as well and some traders sell items in different categories. In Huynh et al.'s model testing, there is only one kind of item

without price differences. In order to simulate the above mentioned real settings and to compare the performance of proposed model with Huynh et al.'s model, two different item situations are simulated. One is the one-Item situation, as what Huynh et al. use; the other is the two-Item situation in which there are two kinds of items; one is priced high and the other priced low.

4.3.3 Three Noise Levels

It is very common that consumers may not have the due knowledge to accurately evaluate the shipped goods and precisely rate the seller. The noise at three noise levels is added to the actual ratings to simulate this observation and test the robustness of different trust models. The added noise all has the same mean of zero but with different deviations of 0, 0.2 and 0.5, respectively. Eventually, all posted ratings are controlled in the range of [-1, +1].

4.3.4 Three FPR Levels

In the E-Marketplace, it is ordinary for consumers not to leave any feedback after an on-line transaction This is due to either the ignorance of the way to post feedback or laziness. This leads to missing data or incomplete information. In order to test the robustness of the trust models with missing data, three FPR levels are devised in the simulation. The FPR is the percentage of buyers who give feedback after the correspoinding transactions. For each model and item situation combination, experiments are also conducted with three FPR levels, which are 100%, 80% and 50%, respectively.

4.4 Simulation Experiment Variables and Parameters

The variables and parameters used in the simulation are as follows.

According to the Distribution of eBay Ratings and the Distribution of Amazon Auction Ratings (Zacharia, 1999), the proportion of positive feedback is rarely less than 80%. In the simulation, there are ten sellers and two for each of the five types of sellers (1GS, 0.8GS, 0.5GS, S1S, S2S) so as to make sure that more satisfactory ratings are posted than the unsatisfactory ones in the mini E-Marketplace. In the mini E-Marketplace, in each run, there are twenty buyers so the number of buyers is greater than that of the sellers, which is a convention in this type of simulation. Each S2S seller has three shills who do not conduct any transaction but post satisfactory ratings for their designated sellers.

The values of the experiment variables are listed in Table 4.1.

Table 4.1 Experiment Variable Table

Variable	Value
Number of Scenarios	10
Number of runs for each scenario	10
Number of buyers	20
Number of sellers	10
- 1GSeller	2
- 0.8GSeller	2
- 0.5GSeller	2
- S1Seller	2
- S2Seller	2
Number of shills for each S2Seller	3

CHAPTER 5

EXPERIMENT RESULTS

In order to evaluate its performance, the proposed trust model is compared with the traditional model and Huynh's model. Between two comparing scenarios, the sequences of the ten OTGs are used to conduct two-tailed paired t-tests to see if the means of the two sequences are significantly different. The CTGs of difference scenarios are also charted to show the trends within model and across models.

The first comparison is to test whether the proposed model helps buyers to select the proper sellers and to obtain a significantly higher mean of buyers' tick gain than with the competing models. To test the significance of the buyer's tick gains across different trust models and to test the robustness of the trust models, two-tailed paired t-tests are carried out across the models and within each model at different noise levels and FPR levels. Similarly, the second comparison is to test the gains of the different kinds of sellers from different trust models and the robustness of different trust models, two-tailed paired t-test is used.

Detailed experiment results are provided in appendices B and C. Appendix B holds all the Across Model Performance Comparison Tables which contain the statistics for across model performance comparison at different noise levels and different FPR levels. And appendix C holds all the Within Model Performance Comparison Tables

which provide the statistics for within model performance comparison at different noise levels and different FPR levels. The titles of the tables are self-explanatory.

The notations in the tables in this chapter and in the appendices are as follows. Avg. represents the CTG of the corresponding buyers or sellers with the corresponding model; Std. represents the standard deviation of the corresponding OTG sequence of the corresponding buyers or sellers with the corresponding model. T, H, and A represent the Traditional model, Huynh's model and the proposed Adaptive Reputation-based Trust model, respectively. P_T and P_H represent the p-values of the corresponding sequences' mean-difference testing with the traditional model and Huynh's model, respectively.

5.1 Buyers' Gains

A good trust model should help the buyers to select proper trustworthy sellers and to gain more in the transactions. If the same holds even in an environment with noise or with incomplete information, the trust model is robust in terms of noise or incomplete information.

5.1.1 In the Situation of One Item

The experiments are conducted to test the performance of the buyers with different trust models, at different noise levels and FPR levels when there is only one kind of item in the E-Marketplace.

5.1.1.1 Buyers' Performance at Different Noise Levels in One-item Situation

As indicated in table 5.1, under the same circumstances with the same noise level, the buyers' tick gains with the proposed model are significant higher than that of

the traditional model and that of the Huynh's model. That means, in the same situation, the buyers equipped with the proposed model yield significant higher gain than those with the competing models.

For the proposed model, there is not much difference between the buyers' tick gains with different noise levels, i.e. the proposed model is robust in one-item situation, in regards of the noise. However, for Huynh's model, when there is noise, the buyers' tick gains are significant lower than that in the situation with no noise (see one-item Huynh Model Noise table in appendix C).

Table 5.1 Buyers' Tick Gain at Different Noise Levels in One-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**51.29057**	**64.53044**	**71.83983**
	Std.	*20.4388*	*13.5494*	*11.6571*
	P_T		2.14E-07	1.86E-12
	P_H			7.64E-05
0.20	**Avg.**	**50.74943**	**58.5793**	**71.56415**
	Std.	*19.4565*	*19.9839*	*12.5913*
	P_T		0.022121	4.44E-11
	P_H			0.000543
0.50	**Avg.**	**51.85883**	**56.73673**	**73.35483**
	Std.	*21.7122*	*22.5624*	*11.434*
	P_T		0.025262	3.77E-13
	P_H			9.9E-06

5.1.1.2 Buyers' Performance at Different FPR Levels in One-item Situation

As shown in table 5.2, under the same circumstance at different FPR levels, the buyers' tick gain with the proposed model is significantly higher than that of the

traditional model and that of the Huynh's model. Buyers benefit significantly more from using the proposed model than by using any of the competing models.

For the proposed model, there is not much difference between the buyers' tick gains at different FPR levels, i.e. the proposed model is robust in one-item situation in regards of the FPR. However, for both the traditional model and Huynh's model, when the FPR level drops, the buyers' tick gains drop significantly (see One-item Traditional Model FPR table and one-item Huynh Model FPR table in appendix C).

Table 5.2 Buyers' Tick Gain at Different FPR Levels in One-item Situation

FPR(%)		Model		
		T	H	A
100	**Avg.**	**51.29057**	**64.53044**	**71.83983**
	Std.	*20.4388*	*13.5494*	*11.6571*
	P_T		2.14E-07	1.86E-12
	P_H			7.64E-05
80	**Avg.**	**46.51467**	**53.92828**	**72.08186**
	Std.	*19.4089*	*19.8262*	*11.9711*
	P_T		0.007664	4.98E-13
	P_H			3.06E-05
50	**Avg.**	**33.3538**	**33.0026**	**74.16986**
	Std.	*18.1193*	*43.384*	*9.47926*
	P_T		0.9142	9.91E-13
	P_H			6.42E-07

5.1.2 In the Situation of Two Items

When there are two kinds of items in the E-Marketplace, one is high-priced and the other is low-priced, the experiments are also conducted to compare the performance of the buyers with different trust models at different noise levels and FPR levels.

5.1.2.1 Buyers' Performance at Different Noise Levels in Two-item Situation

As indicated in table 5.3, under the same circumstances at the same noise level, the buyers' tick gain with the proposed model are significant higher than that of the traditional model and that of Huynh's model. That means, at same noise level in two-item situation, the buyers equipped with the proposed model yield significantly higher gains than those with the competing models.

For the proposed model, in two-item situation, there is not much difference between the buyers' tick gains with different noise levels, i.e. the proposed model is robust in two-item situation, in regards of the noise. However, for Huynh's model, in two-item situation, when there is noise, the buyers' tick gains are lower than that in the base situation (see two-item Huynh Noise table in appendix C).

Table 5.3 Buyers' Tick Gain at Different Noise Levels in Two-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**72.85065**	**90.63083**	**102.2119**
	Std.	*29.3056*	*18.6259*	*16.8652*
	P_T		2.36E-08	1.62E-11
	P_H			8.19E-08
0.20	**Avg.**	**73.26401**	**86.48116**	**101.331**
	Std.	*27.4174*	*22.5109*	*17.6052*
	P_T		2.64E-05	2.79E-09
	P_H			0.000144
0.50	**Avg.**	**74.16427**	**76.44885**	**104.8834**
	Std.	*31.2021*	*46.1071*	*15.3445*
	P_T		0.387416	8.27E-12
	P_H			4.08E-07

5.1.2.2 Buyers' Performance at Different FPR Levels in Two-item Situation

As shown in table 5.4, under the same circumstances at each different FPR level in two-item situation, the buyers' tick gain with the proposed model is significantly higher than that of the traditional model and that of the Huynh's model.

For the proposed model in two-item situation, there is not much difference between the buyers' tick gains at different FPR levels, i.e. the proposed model is robust in two-item situation, in regards of the FPR. However, in two-item situation for both the traditional model and the Huynh's model, when the FPR level drops, the buyers' tick gain significantly drops (see two-item Traditional Model FPR table and two-item Huynh Model FPR table in appendix C).

Table 5.4 Buyers' Tick Gain at Different FPR Levels in Two-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**72.85065**	**90.63083**	**102.2119**
	Std.	*29.3056*	*18.6259*	*16.8652*
	P_T		2.36E-08	1.62E-11
	P_H			8.19E-08
80	**Avg.**	**65.0419**	**77.3198**	**102.4838**
	Std.	*28.8035*	*28.8421*	*17.6421*
	P_T		0.001751	1.5E-14
	P_H			4.23E-06
50	**Avg.**	**47.74139**	**48.44017**	**104.2816**
	Std.	*25.2872*	*36.6925*	*17.1666*
	P_T		0.885589	3.07E-12
	P_H			1.17E-06

5.2 Sellers' Gains

A better trust model should also help the best sellers to gain the most and make the worst sellers' gain the least. If the same holds even in an environment with noise or with incomplete information, the trust model is robust.

5.2.1 Sellers' Performance at Different Noise Levels in One-item Situation

In all the scenarios at different noise levels in one-item situation, 1GSellers are the most favored ones, the S2Sellers are the less favored ones by the proposed model (see all tables in one-item situation in appendix B). This is consistent with the trust settings in the system design, in which 1GSellers are the best and S2Sellers are among the worst in regards to trust. However, for Huynh's model when noise level is 0.5, the tick gain of S2Seller is greater than that of the 1GSeller, which is not consistent with the trust settings (see one-item Ns=p5 table in appendix B). For the traditional model in one-item situation at each different noise level, the S2Sellers' tick gain is always greater than that of the 1Gsellers, which is not consistent with the trust settings, either (see all tables in one-item situation in appendix B).

In summary, at different noise levels in one-item situation the proposed model always favors 1GSellers the most and S2Sellers the least. Huynh's model sometimes favors the 1GSeller the most, sometimes the S2Seller the most. The traditional model always favors the S2Sellers the most. Only the former is consistent with the trust settings.

5.2.1.1 1GSeller's Performance at Different Noise Levels in One-item Situation

As indicated in table 5.5, at each noise level in one-item situation, the 1GSellers' tick gain of the proposed model is significantly higher than that of the traditional model.

When the noise level is 0.2 or 0.5 in one-item situation, there is no significant difference between the 1GSellers' tick gain of the proposed model and that of Huynh's model. But in the base scenario in one-item situation, 1GSellers' tick gain of Huynh's model is significantly higher than that of the proposed model.

When the noise level is 0% and 20% in one-item situation, 1GSellers' tick gain of Huynh's model is significantly higher than that of the traditional model.

Table 5.5 1GSellers' Tick Gain at Different Noise Levels in One-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**18.35596**	**34.41061**	**25.04847**
	Std.	*4.5759*	*5.24103*	*4.52744*
	P_T		3.77E-10	1.13E-07
	P_H			4.34E-07
0.2	**Avg.**	**18.00144**	**28.20422**	**24.46035**
	Std.	*4.75639*	*6.16699*	*4.76131*
	P_T		0.022371	6.21E-06
	P_H			0.301641
0.5	**Avg.**	**14.76146**	**23.46491**	**21.05069**
	Std.	*4.51156*	*4.669*	*4.93889*
	P_T		0.098714	5.37E-07
	P_H			0.613722

5.2.1.2 S2Seller's Performance at Different Noise Levels in One-item Situation

As indicated in table 5.6, in one-item situation at the same noise level, the S2Sellers' tick gain of the proposed model is always significantly lower than that of Huynh's model and that of the traditional model.

In one-item situation, noise does not have significant impact on the S2Sellers' tick gain of the proposed model (see one-item Adaptive Trust Model FPR table in appendix C).

Table 5.6 S2Sellers' Tick Gain with Different Noise Levels in One-Item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**32.44236**	**16.07179**	**0.964437**
	Std.	*20.0464*	*13.0312*	*3.06525*
	P_T		3.9E-10	3.33E-17
	P_H			1.38E-09
0.2	**Avg.**	**32.2682**	**25.21085**	**0.975303**
	Std.	*19.3747*	*20.3567*	*3.23804*
	P_T		0.174203	3.6E-14
	P_H			0.001191
0.5	**Avg.**	**35.05346**	**26.22787**	**1.304229**
	Std.	*22.0401*	*18.2517*	*3.50291*
	P_T		0.717203	4.48E-15
	P_H			0.000437

5.2.1.3 S1Seller's Performance at Different Noise Levels in One-item Situation

As indicated in table 5.7, in one-item situation at the same noise level, the S1Sellers' tick gain of the proposed model is significantly higher than that of Huynh's model and that of the traditional model.

Table 5.7 S1Sellers' Tick Gain at Different Noise Levels in One-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**12.08234**	**1.202089**	**14.17152**
	Std.	*9.76169*	*2.65694*	*11.3269*
	P_T		1.01E-10	3.76E-05
	P_H			1.15E-10
0.2	**Avg.**	**12.30554**	**2.150998**	**14.76773**
	Std.	*10.1669*	*4.23554*	*11.6402*
	P_T		4.35E-08	0.00074
	P_H			1.21E-09
0.5	**Avg.**	**13.00586**	**1.451511**	**16.45427**
	Std.	*9.55616*	*2.493*	*10.172*
	P_T		4.71E-12	9.95E-06
	P_H			1.32E-10

Since the proposed model cannot tell whether the misbehavior of the S1Seller is on purpose to abuse reputation or due to unintentional mistakes, the trust value of an S1Seller can be higher than that of a 0.8GSeller.

5.2.2 Sellers' Performance with Different FPR Levels in One-item Situation

In all the scenarios with one-item situation at different FPR levels, 1GSellers are the most favored ones and the S2Sellers are the least favored ones by the proposed model. This is consistent with the trust settings. However, for Huynh's model when the FPR level is 80% or 50%, the tick gain of S2Seller is greater than that of the 1GSeller, which is not consistent with the trust settings (see one-item FPR=p8 table and one-item FPR=p5 table in appendix B). For the traditional model in one-item situation at the same FPR level, S2Sellers' tick gain is always greater than that of the 1Gsellers, which is not consistent with the trust settings, either (see all the tables in one-item situation in

appendix B). In summary, in one-item situation at different FPR level, the proposed model always consistent with the trust settings; Huynh's model sometimes; and the traditional model never.

5.2.2.1 1GSeller's Performance at Different FPR Levels in One-item Situation

As indicated in table 5.8, in one-item situation and at the FPR level of 50%, the 1GSellers' tick gain of the proposed model is significantly better than that of the traditional model and that of the Huynh's model. At the FPR level of 80%, there is no significant difference between the 1GSellers's tick gain of the proposed model and that of Huynh's model; however, in the base scenario in one-item situation, the 1GSellers' tick gain of the Huynh's model is significantly higher than that of the proposed model.

In one-item situation at the same FPR levels, the 1GSellers' tick gain of the proposed model is significantly higher than that of the traditional model.

Table 5.8 1GSellers' Tick Gain at Different FPR Levels in one-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**18.35596**	**34.41061**	**25.04847**
	Std.	*4.5759*	*5.24103*	*4.52744*
	P_T		3.77E-10	1.13E-07
	P_H			4.34E-07
80	**Avg.**	**17.93658**	**27.26582**	**25.57933**
	Std.	*4.53368*	*6.27528*	*4.44767*
	P_T		0.008965	2.84E-08
	P_H			0.601407
50	**Avg.**	**17.53423**	**9.735722**	**31.53402**
	Std.	*4.61853*	*3.04443*	*4.27359*
	P_T		0.10754	1.68E-09
	P_H			0.000902

5.2.2.2 S2Seller's Performance at Different FPR Levels in One-item Situation

As indicated in table 5.9, in one-item situation at the same FPR level, the S2Sellers' tick gain of the proposed model is significantly lower than that of Huynh's model and that of the traditional model. As the worst seller in regards to trust, S2Seller is least favored among all the sellers by the proposed model at different FPR levels in one-item situation.

In one-item situation, FPR does not have significant impact on S2Sellers' tick gain of the proposed model (see one-item Adaptive Trust Model FPR table in appendix C).

Table 5.9 S2Sellers' Tick Gain at Different FPR Levels in One-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**32.44236**	**16.07179**	**0.964437**
	Std.	*20.0464*	*13.0312*	*3.06525*
	P_T		3.9E-10	3.33E-17
	P_H			1.38E-09
80	**Avg.**	**37.31686**	**23.86322**	**1.129435**
	Std.	*20.4678*	*15.605*	*3.48839*
	P_T		0.093848	1.7E-14
	P_H			0.000201
50	**Avg.**	**51.45589**	**65.57606**	**1.427003**
	Std.	*20.6981*	*40.1525*	*3.71782*
	P_T		0.024972	9.66E-13
	P_H			7E-06

5.2.2.3 S1Seller's Performance at Different FPR Levels in One-item Situation

As indicated in table 5.10, in one-item situation at the same FPR level, the S1Sellers' tick gain of the proposed model is always significantly higher than that of the

Huynh's model and that of the traditional model. This can be explained as in section 5.2.1.3.

Table 5.10 S1Seller's Tick Gain at Different FPR Levels in One-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**12.08234**	**1.202089**	**14.17152**
	Std.	*9.76169*	*2.65694*	*11.3269*
	P_T		1.01E-10	3.76E-05
	P_H			1.15E-10
80	**Avg.**	**11.99248**	**2.276527**	**13.95589**
	Std.	*9.32337*	*3.81472*	*10.8381*
	P_T		3.46E-10	5.5E-05
	P_H			1.83E-10
50	**Avg.**	**11.80662**	**1.416238**	**7.54163**
	Std.	*10.1*	*2.92802*	*7.73826*
	P_T		4.43E-09	0.000209
	P_H			1.23E-06

5.2.3 Sellers' Performance at Different Noise Levels in Two-item Situation

As in one-item, in all the scenarios at different noise levels in two-item situation, 1GSellers are the most favored ones the S2Sellers are the less favored ones by the proposed model (see tables in two-item situation at different noise levels in appendix B). This consists with the trust settings, except that at noise level of 0.2 in two-item situation, the 0.5GSellers' tick gains are not significantly different from that of the S2Sellers. However. for Huynh's model, when noise level is 0.5, the tick gain of S2Seller is significantly greater than that of the 1GSeller, which is not consistent with the trust settings (see two-item Ns=p5 table in appendix B). For the traditional model at each different noise level, the S2Sellers' tick gain is always significantly greater than

that of the 1Gsellers, which is not consistent with the trust settings, either (see tables in two-item situation at different noise levels in appendix B).

In summary, at different noise levels in two-item situation, the proposed model always favors 1GSellers sellers the most and S2Sellers the least. Huynh's model sometimes favors the 1GSeller the most, sometimes favors the S2Seller the most; the traditional model always favors the S2Seller the most. As to the tick gains of the 1GSellers and that of the S2Sellers, only the proposed model is consistent with the trust settings.

5.2.3.1 1GSeller's Performance at Different Noise Levels in Two-item Situation

As indicated in table 5.11, at each noise level in two-item situation, the 1GSellers' tick gain of the proposed model is significantly higher than that of the traditional model. When the noise level is 0.5, there is no significant difference between the 1GSellers' tick gain of the proposed model and that of the Huynh's model.

Table 5.11 1GSellers' Tick Gain at Different Noise Levels in Two-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**26.26353**	**49.09343**	**35.8014**
	Std.	*7.21318*	*7.08792*	*7.02832*
	P_T		3.8E-11	1.27E-08
	P_H			3.52E-11
0.2	**Avg.**	**26.90946**	**46.57027**	**37.32138**
	Std.	*7.08047*	*9.60838*	*7.2045*
	P_T		1.44E-08	2.17E-05
	P_H			0.000118
0.5	**Avg.**	**21.78439**	**20.1078**	**30.76169**
	Std.	*6.88239*	*4.90703*	*7.22941*
	P_T		0.82258	6.15E-09
	P_H			0.18246

5.2.3.2 S2Seller's Performance at Different Noise Levels in Two-item Situation

As in one-item situation with noise, as indicated in bable 5.12, at the same noise levels in two-item situation, the S2Sellers' tick gain of the proposed model is always significantly lower than that of Huynh's model and that of the traditional model.

As in one-item situation, noise does not have significant impact on the S2Sellers' tick gain of the proposed model in two-item situation (see two-item Adaptive Trust Model Noise table in appendix C).

Table 5.12 S2Sellers' Tick Gain at Different Noise Levels in Two-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**46.04173**	**25.73869**	**1.265371**
	Std.	*28.2527*	*19.9062*	*4.33418*
	P_T		8.68E-11	6.61E-16
	P_H			3.02E-13
0.2	**Avg.**	**45.46162**	**29.73216**	**3.885071**
	Std.	*27.3365*	*22.8357*	*6.33524*
	P_T		7.61E-08	5.94E-08
	P_H			1.86E-05
0.5	**Avg.**	**50.2928**	**64.29635**	**1.761626**
	Std.	*32.5899*	*45.812*	*5.05534*
	P_T		0.10316	1.03E-13
	P_H			6.91E-05

5.2.3.3 S1Seller's Performance at Different Noise Levels in Two-item Situation

As indicated in table 5.13, in two-item situation at the same noise level the S1Sellers' tick gain of the of the proposed model is significantly higher than that of Huynh's model. Explanation can be the same as in section 5.2.13.

Table 5.13 S1Seller's Tick Gain at Different Noise Levels in Two-item Situation

Noise		Model		
		T	H	A
0	**Avg.**	**16.78098**	**1.414586**	**19.46014**
	Std.	*14.2649*	*3.35683*	*15.8278*
	P_T		8.75E-13	6.22E-06
	P_H			4.73E-14
0.2	**Avg.**	**17.25023**	**2.300702**	**18.33734**
	Std.	*13.7873*	*4.66253*	*14.5382*
	P_T		1.67E-10	0.587144
	P_H			1.18E-05
0.5	**Avg.**	**17.88053**	**1.756297**	**22.52343**
	Std.	*11.8731*	*3.33192*	*12.7528*
	P_T		2.58E-10	2.82E-05
	P_H			8.21E-11

5.2.4 Sellers' Performance at Different FPR Levels in Two-item Situation

As in one-item situation, in all the scenarios with two-item situation at different FPR levels, 1GSellers are the most favored ones and the S2Sellers are the least favored ones by the proposed model. This is consistent with the trust settings, except that at FPR level of 50% in two-item situation, the 0.5GSellers' tick gain is not significantly different from that of the S2Seller. However, for Huynh's model when the FPR level is 80% or 50%, the tick gain of S2Seller is greater than that of the 1GSeller. This is not consistent with the trust settings (see two-item FPR=p8 table and two-item FPR=p5 table in appendix B). For the traditional model, at the same FPR level in two-item situation, the S2Sellers' tick gain is always greater than those of the 1Gsellers, which is not consistent with the trust settings (see tables in two-item situation at different level of FPR in appendix B). In summary, in two-item situation at different FPR level, the

proposed model always favors 1GSellers the most and S2Sellers the least (S2Sellers are among the least). Huynh's model sometimes favors the 1GSeller the most and sometimes the S2Seller is most favored. The traditional model always favors the S2Sellers the most.

5.2.4.1 1GSeller's Performance at Different FPR Levels in Two-item Situation

As indicated in table 5.14, in two-item situation, at the FPR level of 80% or 50%, there is no significant difference between the 1GSellers' tick gain of the proposed model and that of Huynh's model. However; in the base scenario in two-item situation, the 1GSellers' tick gain of Huynh's model is significantly higher than that of the proposed model.

In two-item situation, at the same FPR level, the 1GSellers' tick gain of the proposed model is significantly higher than that of the traditional model.

Table 5.14 1GSeller's Tick Gain at Different FPR Levels in Two-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**26.26353**	**49.09343**	**35.8014**
	Std.	*7.21318*	*7.08792*	*7.02832*
	P_T		3.8E-11	1.27E-08
	P_H			3.52E-11
80	**Avg.**	**25.91669**	**40.31754**	**36.0589**
	Std.	*7.09894*	*8.44778*	*7.18985*
	P_T		0.012029	9.19E-08
	P_H			0.364287
50	**Avg.**	**25.12011**	**29.53447**	**40.1184**
	Std.	*6.8019*	*6.48281*	*7.08328*
	P_T		0.447082	3.96E-09
	P_H			0.083602

5.2.4.2 S2Seller's Performance at Different FPR Levels in Two-item Situation

As indicated in table 5.15, the S2Sellers' tick gain of the proposed model is significantly lower than that of Huynh's model and that of the traditional model. As the worst seller in regards to trust, S2Seller is least favored among all sellers by the proposed model with different FPR levels in two-item situation.

In two-item situation, FPR does not have significant impact on S2Sellers' tick gain of the proposed model (see two-item Adaptive Trust Model FPR table in appendix C).

Table 5.15 S2Sellers' Tick Gain at Different FPR Levels in Two-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**46.04173**	**25.73869**	**1.265371**
	Std.	*28.2527*	*19.9062*	*4.33418*
	P_T		8.68E-11	6.61E-16
	P_H			3.02E-13
80	**Avg.**	**53.71692**	**47.32567**	**1.503437**
	Std.	*28.9278*	*31.1428*	*4.88129*
	P_T		0.228187	2.55E-16
	P_H			0.000229
50	**Avg.**	**72.86958**	**76.60269**	**2.327695**
	Std.	*28.5195*	*35.555*	*5.80031*
	P_T		0.276071	2.1E-14
	P_H			1.31E-05

5.2.4.3 S1Seller's Performance at Different FPR Levels in Two-item Situation

As indicated in Table 5.16, in two-item situation at the same FPR level, the S1Sellers' tick gain of the proposed model is significantly higher than that of the Huynh's model and that of the traditional model, except at the FPR level of 50%.

Table 5.16 S1Sellers' Tick Gain at Different FPR Levels in Two-item Situation

FPR (%)		Model		
		T	H	A
100	**Avg.**	**16.78098**	**1.414586**	**19.46014**
	Std.	*14.2649*	*3.35683*	*15.8278*
	P_T		8.75E-13	6.22E-06
	P_H			4.73E-14
80	**Avg.**	**17.34125**	**2.20732**	**19.53084**
	Std.	*13.3755*	*4.2393*	*16.1415*
	P_T		1.99E-09	0.003549
	P_H			4.37E-10
50	**Avg.**	**16.08402**	**2.424645**	**17.47901**
	Std.	*12.3262*	*4.02442*	*15.6032*
	P_T		5.77E-07	0.160209
	P_H			2.22E-06

5.2.5 Summary of the Sellers' Gains

In all scenarios, only the proposed model retains that the 1GSellers are favored most and the S2Sellers are favored the least, which consists with the trust settings. In some scenarios, both Huynh's model and the traditional model or either of them is favors S2Sellers other than 1GSellers, which is not consistent with the trust settings. Even though in some scenarios, 1Gsellers' tick gain with the proposed model is significantly less than that with Huynh's model and/or S1Seller's gain with the proposed model is significantly higher than that with the Huynh's model. The proposed model can defeat the S2Sellers well but neither of the competing models.

Overall, the proposed model is better than Huynh's model, and Huynh's model is better than the traditional model in terms of Sellers' gains and robustness.

5.3 Significant Trends within Models

This research also finds significant treads about buyers' tick gains and the sellers' tick gains when the FPR level changes. FPR level has significant impact on the performance of buyers and sellers in the mini E-Marketplace. But for the proposed model, there is no significant tread about the buyers or the sellers.

5.3.1 Significant Trends with the Traditional Model

The data of one-item Traditional Model FPR table and two-item Traditional Model FPR table in appendix C reveal significant trends with the traditional model about the buyers' tick gains and S2Sellers' tick gains with the change of FPR level, which are depicted in figure 5.1. When the FPR level drops, the buyers' tick gains both in one-item situation and two-item situation also drop significantly; however the S2Sellers' tick gains increased significantly. The drop of the FPR level significantly causes buyers' tick gain decrease both in one-item situation and two-item situation. The drop of the FPR level causes significant S2Sellers' tick gain increase both in one-item situation and two-item situation.

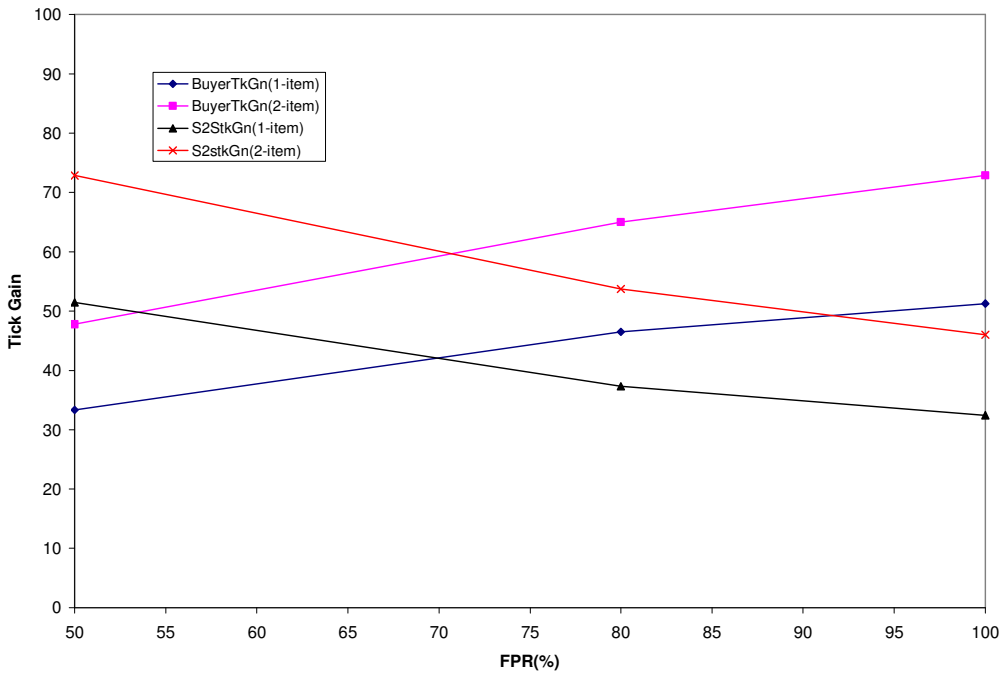

Figure 5.1 Significant Trends with the Traditional Model

5.3.2 Significant Trends with Huynh's Model

The data of one-item Huynh Model FPR table and two-item Huynh Model FPR table in appendix C also reveal significant trends with Huynh's model about the buyers' tick gains, 1GSellers' tick gains and S2Sellers' tick gains with the change of FPR level, which are charted in figure 5.2. When the FPR level drops, the buyers' tick gains both in one-item situation and two-item situation also drop significantly; and 1GSellers' tick gain in one-item situation also drops significantly. However, S2Sellers' tick gain in one-item situation increases significantly. The drop of the FPR level causes significantly buyers' tick gain decrease both in one-item situation and two-item situation; and the drop of the FPR level causes significant S2Sellers' tick gain increase both in one-item

situation; and the drop of the FPR level cause significant 1GSellers' tick gain increase in one-item situation.

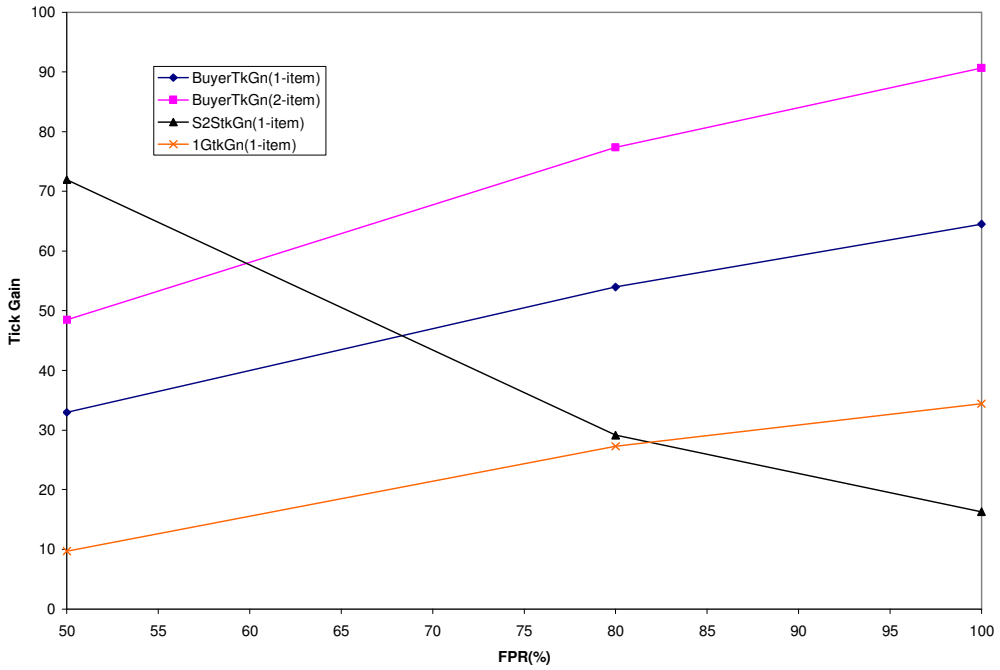

Figure 5.2 Significant Trends with the Huynh's Model

5.4 Comparison of Buyers' Performance Trends across Models

The trends of the buyers' performance are compared across the proposed model and the competing models.

5.4.1 Buyers' Performance Trends across Models with Noise

In all scenarios at the same noise levels, as revealed in figures 5.3 and 5.4, the buyers' tick gains of the proposed model are significantly higher than that of the traditional model and that of Huynh's model. Noise has certain impact on all the models but to different degrees. When noise level increases, the buyers' tick gain of Huynh's model decreases. Overall, the noise has the least impact on the buyers' tick gain of the

proposed model. Under the same circumstance at the same noise level, the buyers' tick gain of the proposed model is significantly higher than that of the competing models.

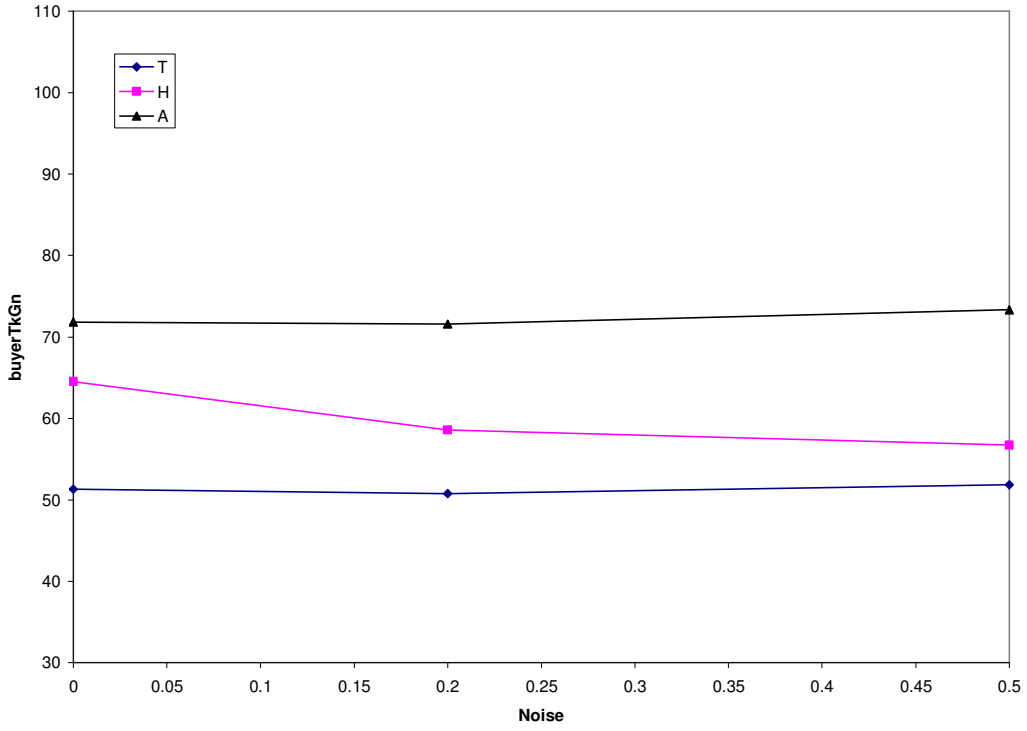

Figure 5.3 Trends of Buyers' Performance with Noise in One-item Situation

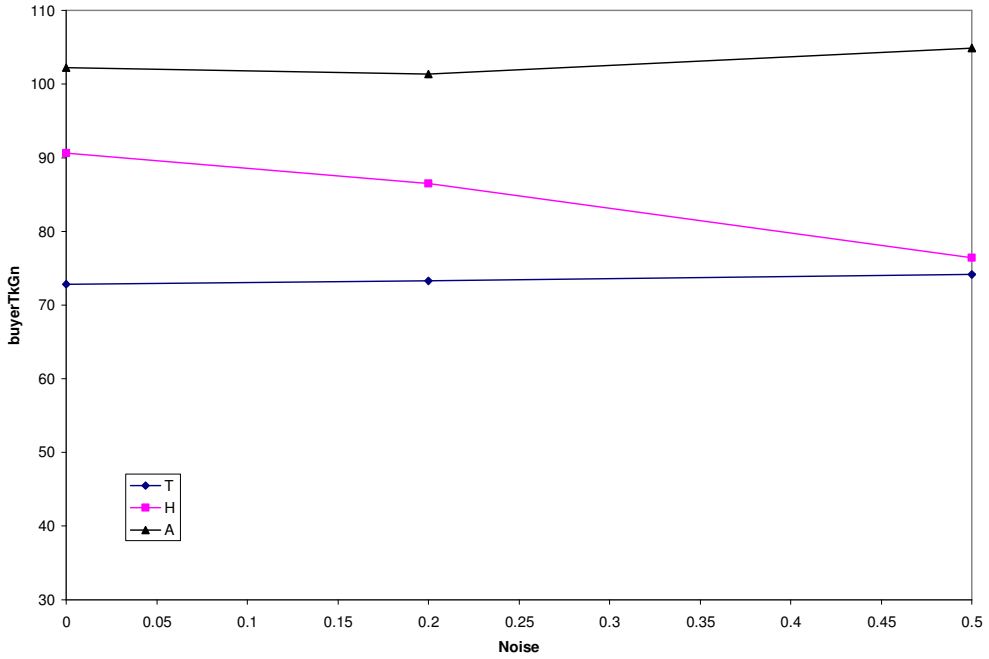

Figure 5.4 Trends of Buyers' Performance with Noise in Two-item Situation

5.4.2 Buyers' Performance Trends across Models with FPR

In all scenarios at different levels of FPR, as revealed in figures 5.5 and 5.6, the buyers' tick gains of the proposed model are significantly higher than that of the traditional model and that of Huynh's model. FPR has certain impact on all the models but to different degrees. When the FPR level increases, the buyers' tick gain of Huynh's model and that of the traditional model increase. Overall, the FPR level has the least impact on the buyers' tick gain of the proposed model. Under the same circumstance at the same level of FPR, the buyer's tick gain of the proposed model is significantly higher than that of the competing models.

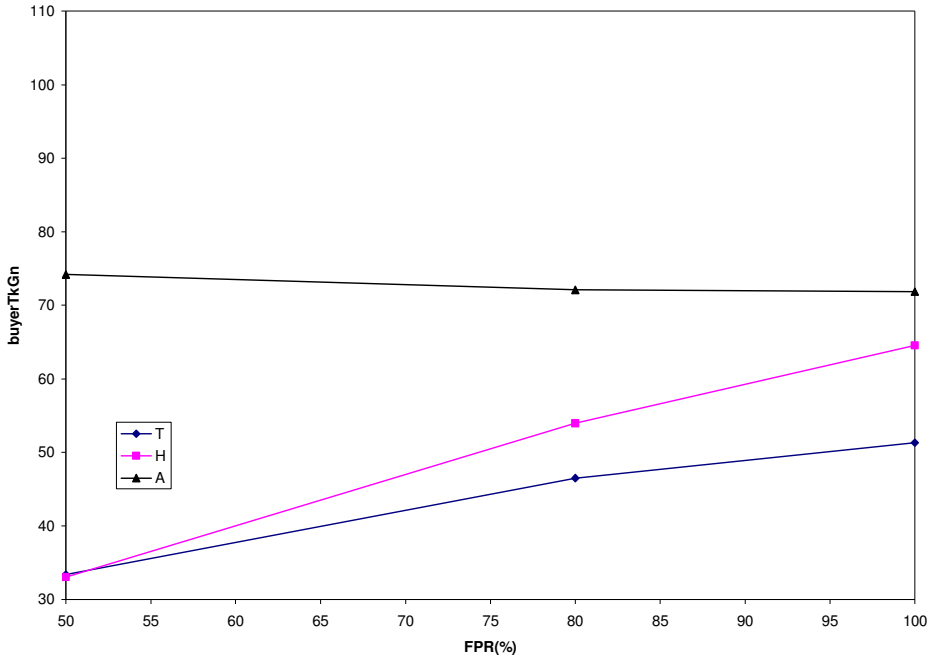

Figure 5.5 Trends of Buyers' Performance with FPR in One-item Situation

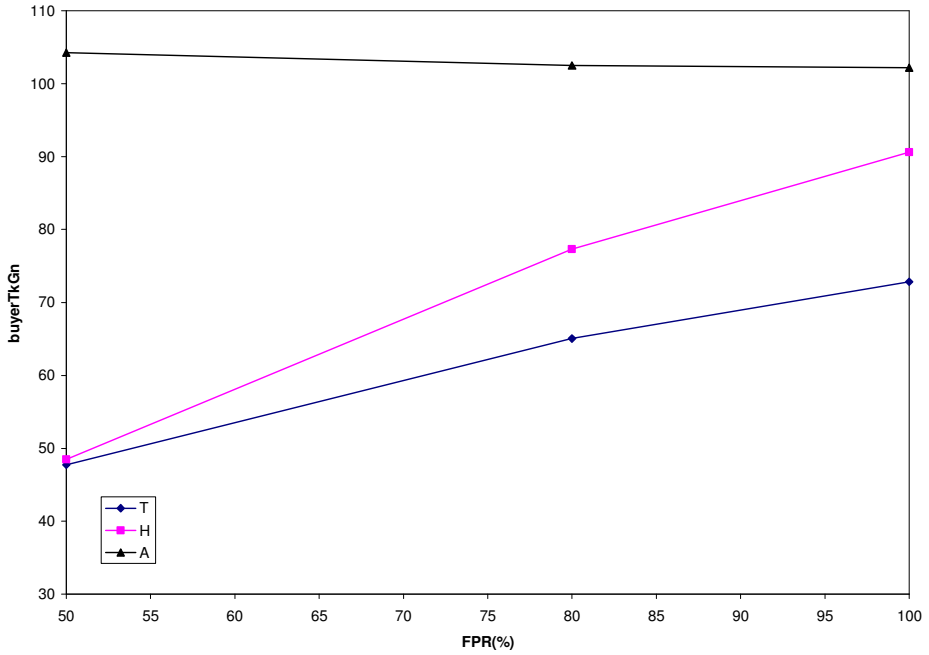

Figure 5.6 Trends of Buyers' Performance with FPR in Two-item Situation

5.4.3 Summary of Buyers' Performance Trends across Models

In all scenarios under the same circumstance, the buyers' tick gain of the proposed model is significantly higher than that of the traditional model and that of Huynh's model. Noise and FPR have certain impact on all the models but to different degrees. Overall, the noise and FPR have the least impact on the buyers' tick gain of the proposed model. Under the same circumstance, the buyer's tick gain of the proposed model is significantly higher than that of the competing models.

5.5 Comparison of Sellers' Performance Trends across Models

The trends of the sellers' performance are compared across the proposed model and the competing models. Since the behavior of 1GSellers, S1Sellers and S2Sellers are most interesting, the across-model performance trends of 0.8GSeller and 0.5GSeller are not included in the comparison.

5.5.1 Comparison of 1GSellers' Performance Trends across Models

In the following, 1GSellers' performance trends with the noise levels and FPR levels are compared across the proposed model and the competing models, respectively.

5.5.1.1 1GSellers' Performance Trends across Models with Noise Levels

As charted in figures 5.7 and 5.8, when the noise level increases, the 1GSellers' tick gain decreases with all the models. In most of the scenarios, the 1GSellers' tick gains of Huynh's model are higher than that of the proposed model and the traditional model.

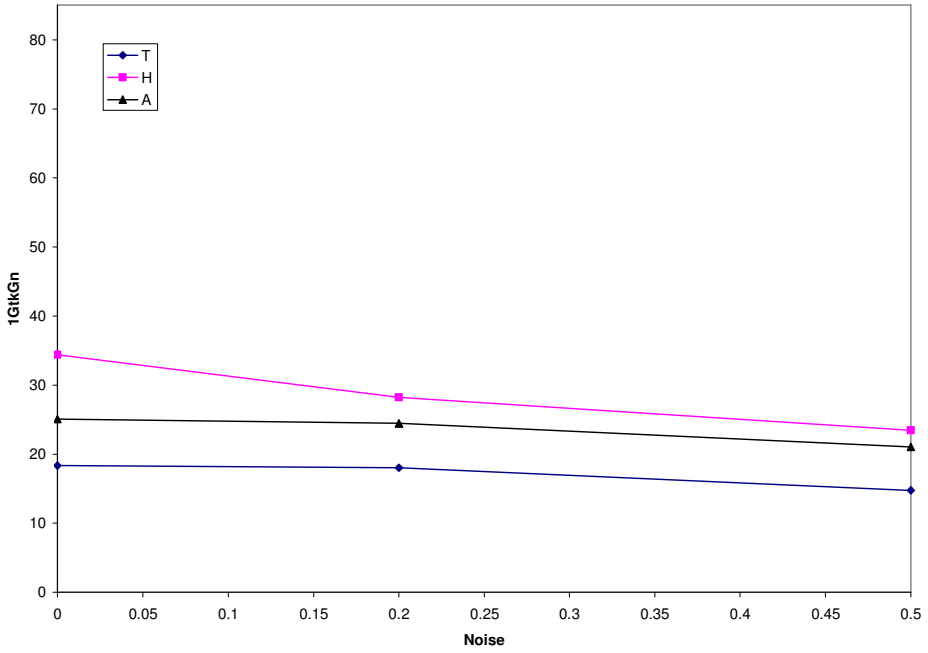

Figure 5.7 Trends of 1GSellers' Performance with Noise Levels in One-item Situation

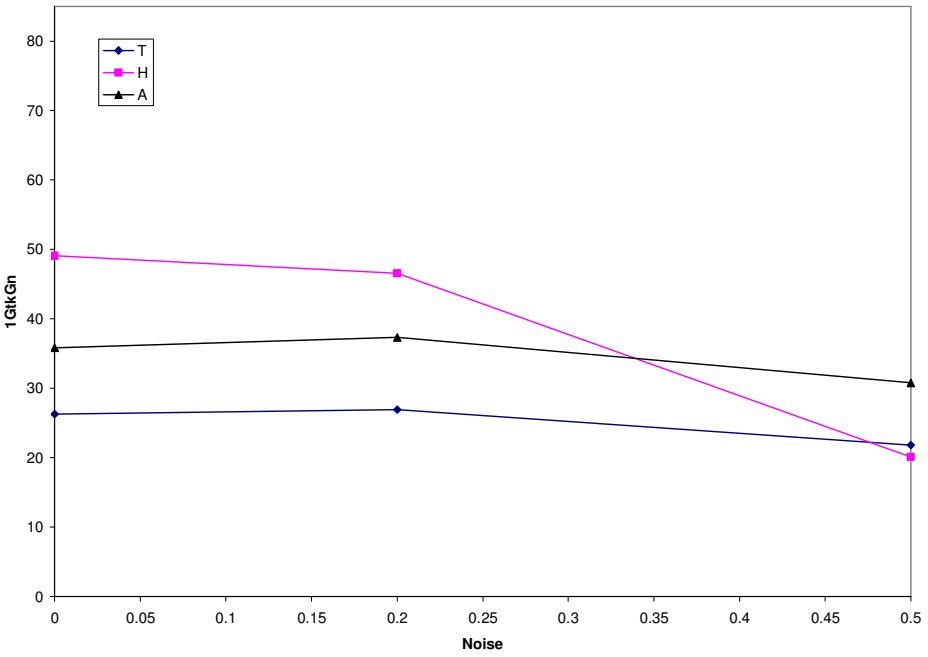

Figure 5.8 Trends of 1GSellers' Performance with Noise in Two-item Situation

5.5.1.2 1GSellers' Performance Trends across Models with FPR Levels

As shown in figures 5.9 and 5.10, when the FPR increase, the 1GSellers's tick gain tends to increase both with Huynh's model and the traditional model; however, with the proposed model, the 1GSellers's tick gain slightly tends to decrease.

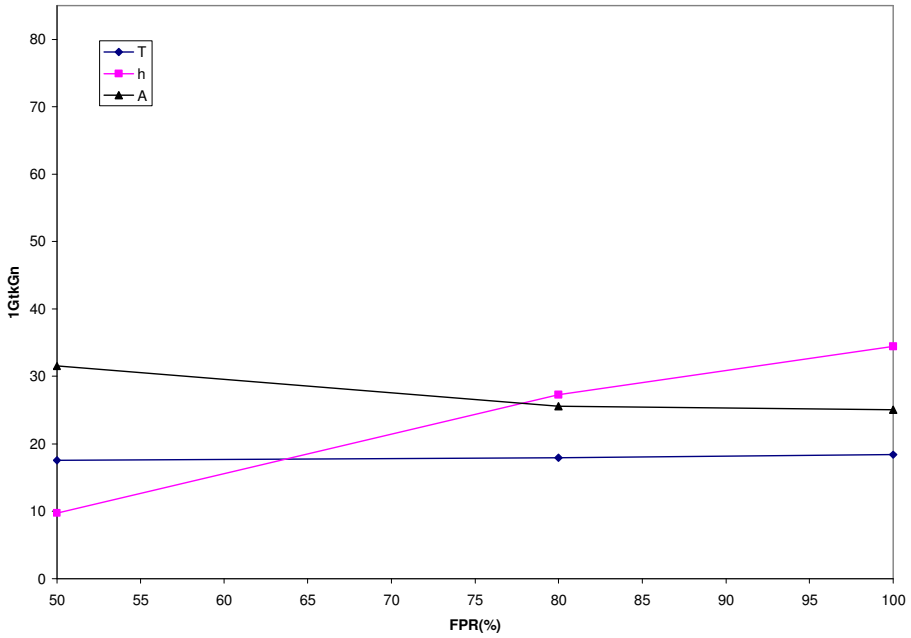

Figure 5.9 1GSellers' Performance Trends with FPR in One-item Situation

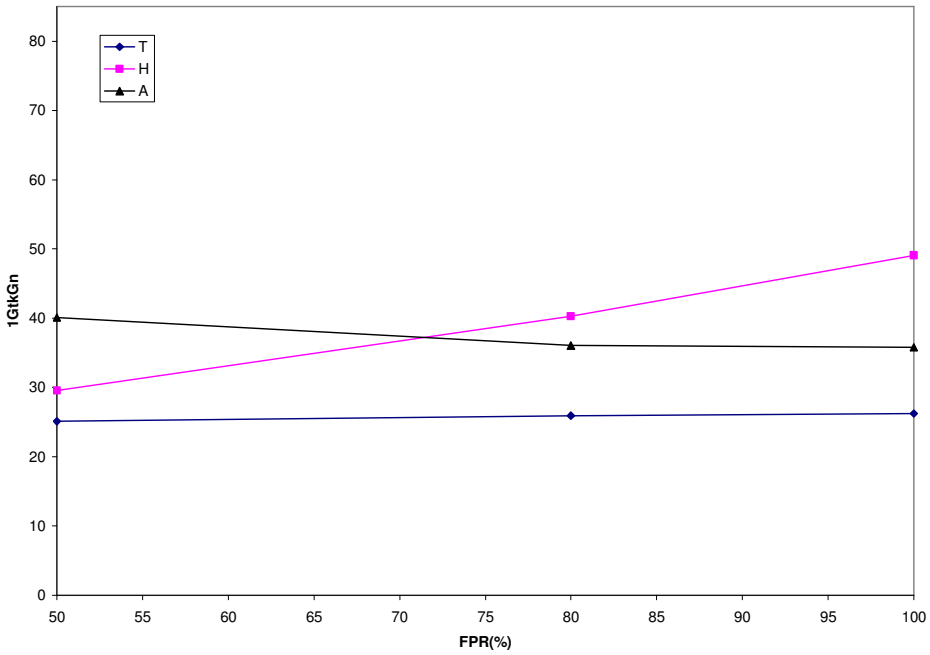

Figure 5.10 1GSellers' Performance Trends with FPR in Two-item Situation

5.5.2 S2Sellers' Performance Trends across Models

In the following, S2Sellers' performance trends with the noise levels and FPR levels are compared across the proposed model and the competing models, respectively.

5.5.2.1 S2Sellers' Performance Trends across Models with Noise Levels

As indicated in figures 5.11 and 5.12, the change of noise level has strong impact on the S2Sellers' tick gain of Huynh's model, but slight impact on that of the proposed model and that of the traditional model.

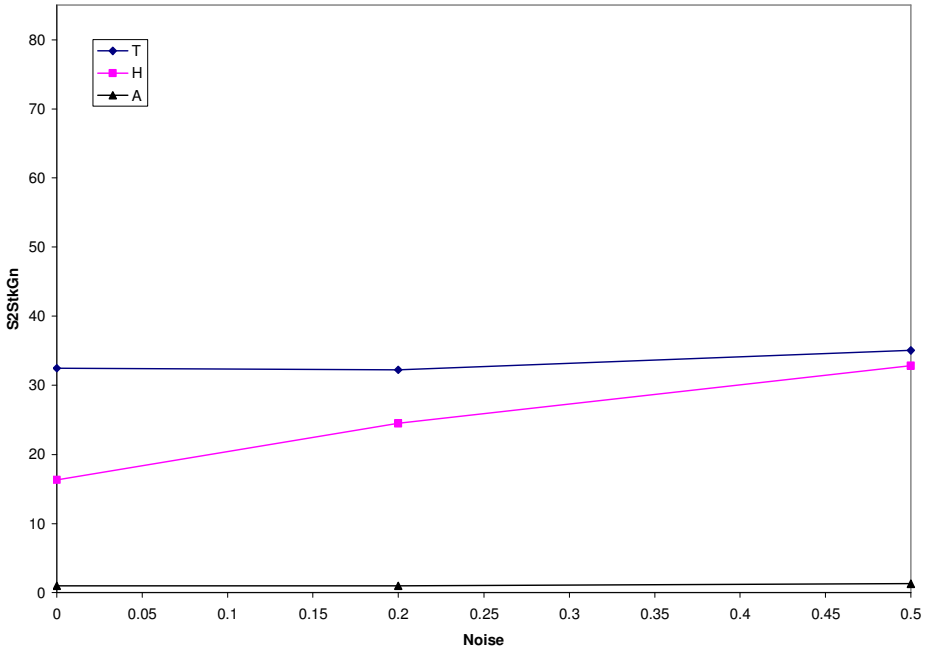

Figure 5.11 S2Sellers' Performance Trends with Noise in One-item Situation

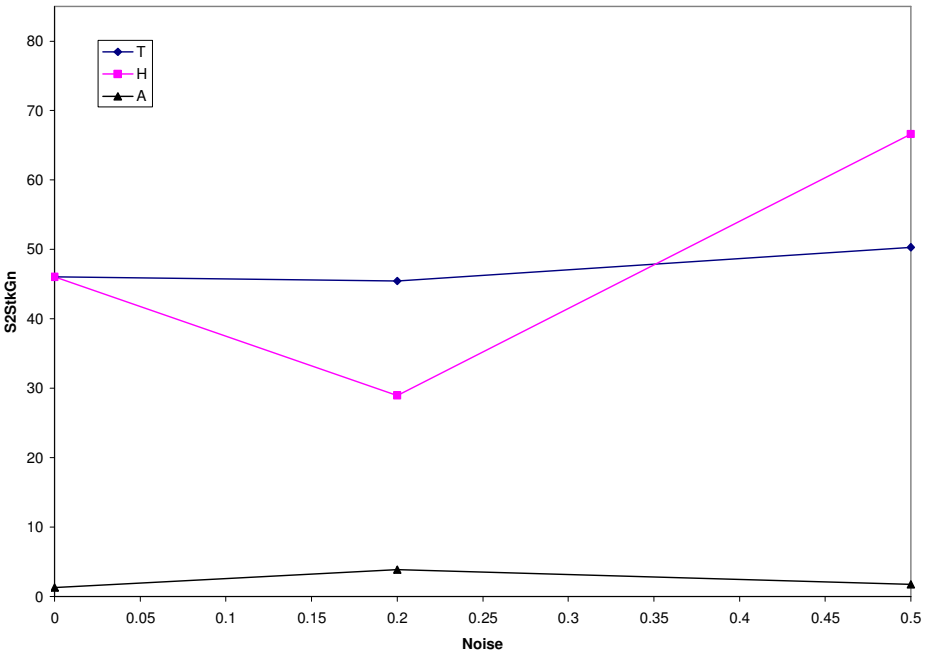

Figure 5.12 S2Sellers' Performance Trends with Noise in Two-item Situation

5.5.2.2 S2Sellers' Performance Trends across Models with FPR Levels

As charted in figures 5.13 and 5.14, the change of FPR level has strong impact on the S2Sellers' tick gain of Huynh's model and that of the traditional model, but slight impact on that of the proposed model. When the FPR level increases, the S2Sellers' tick gains of Huynh's model and that of the traditional model decrease.

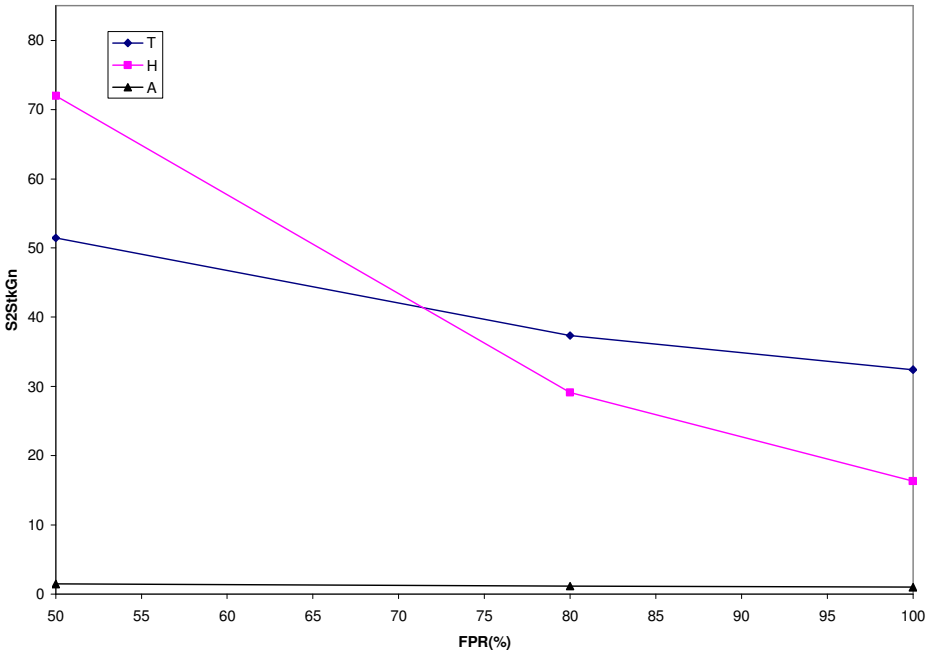

Figure 5.13 S2Sellers' Performance Trends with FPR in One-item Situation

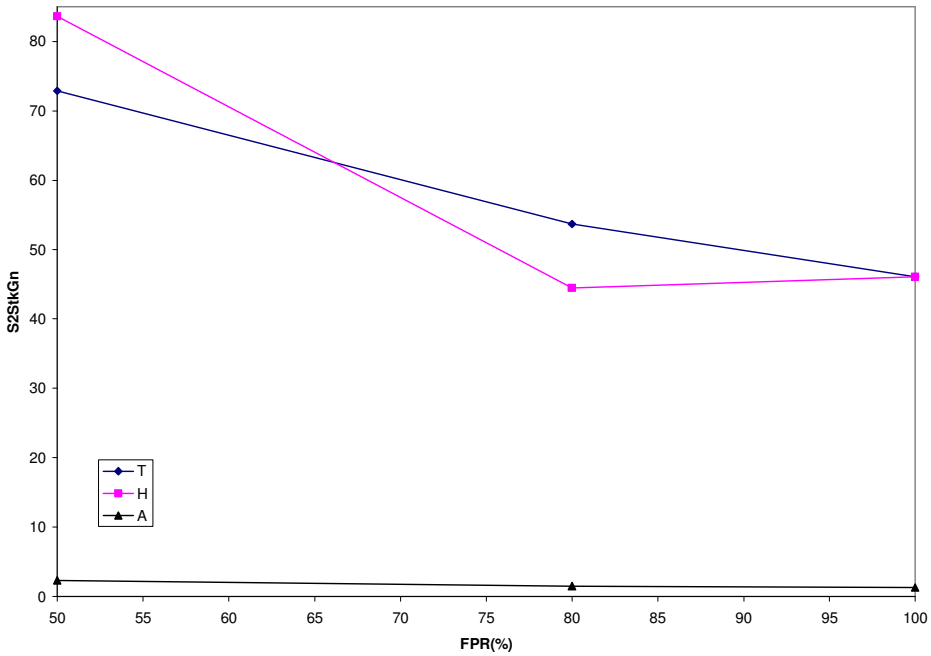

Figure 5.14 S2Sellers' Performance Trends with FPR in Two-item Situation

5.5.3 S1Sellers' Performance Trends across Models

In the following, S1Sellers' performance trends with the noise levels and FPR levels are compared across the proposed model and the competing models, respectively.

5.5.3.1 S1Sellers' Performance Trends across Models with Noise Levels

As depicted in figures 5.15 and 5.16, the change of noise level has slight impact on the S1Sellers' tick gains with all models. When the noise level increases, the S1Sellers' tick gain of the traditional model tends to increase slightly.

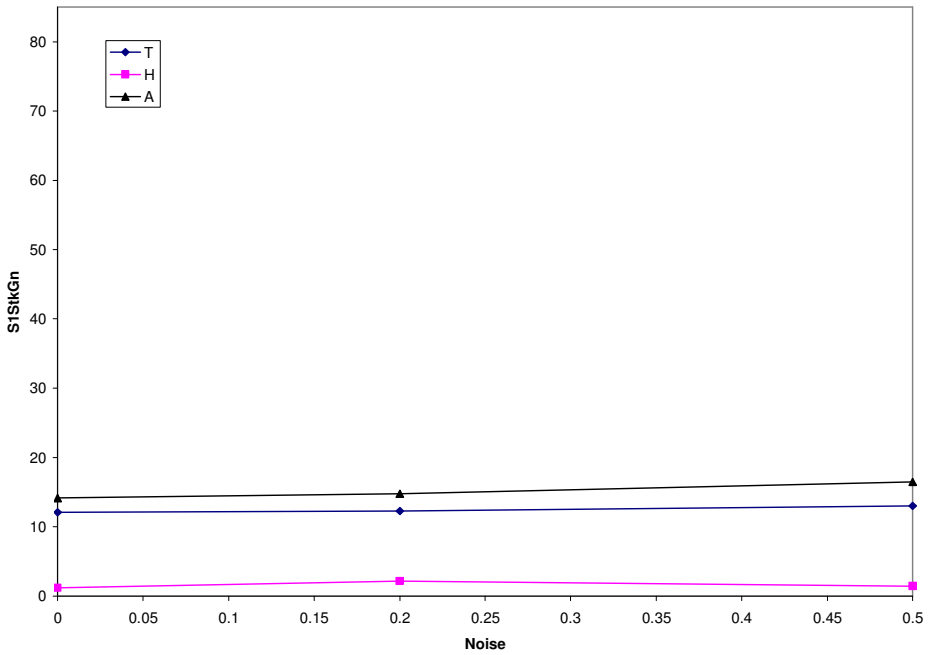

Figure 5.15 S1Sellers' Performance Trends with Noise in One-item Situation

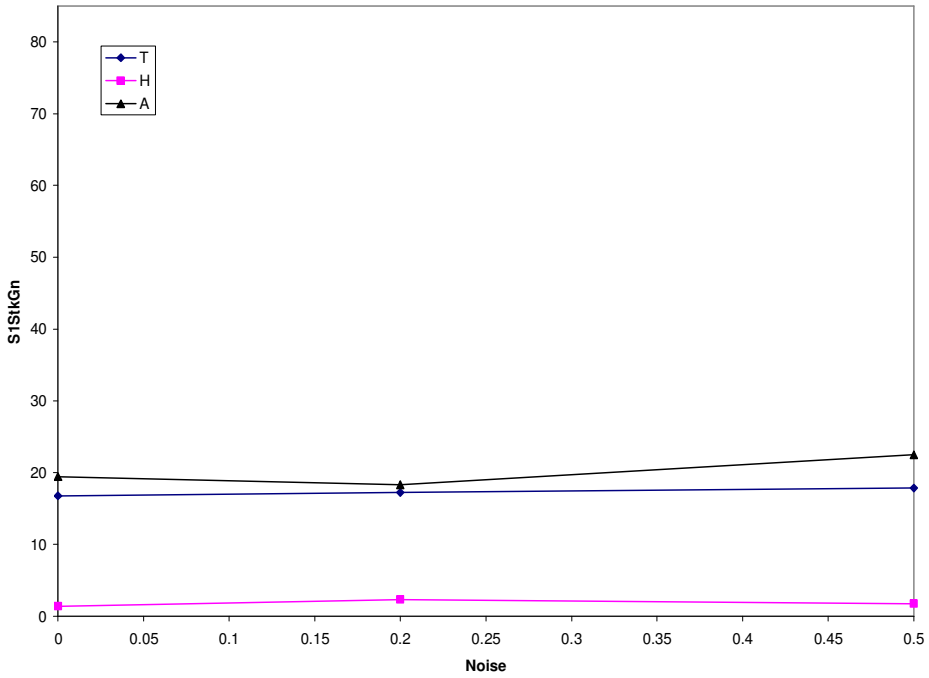

Figure 5.16 S1Sellers' Performance Trends with Noise in Two-item Situation

5.5.3.2 S1Sellers' Performance Trends across Models with FPR Levels

As shown in figures 5.17 and 5.18, the change of FPR level has slight impact on the S1Sellers' tick gains with all models. When the FPR level increases, the S1Sellers' tick gain of the proposed model tends to increase slightly.

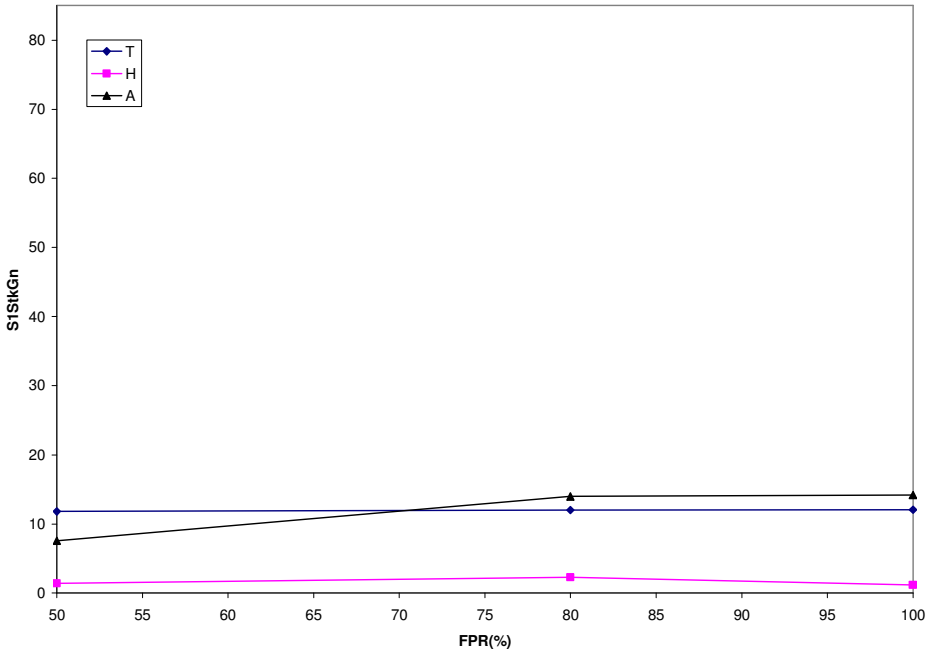

Figure 5.17 S1Sellers' Performance Trends with FPR in One-item Situation

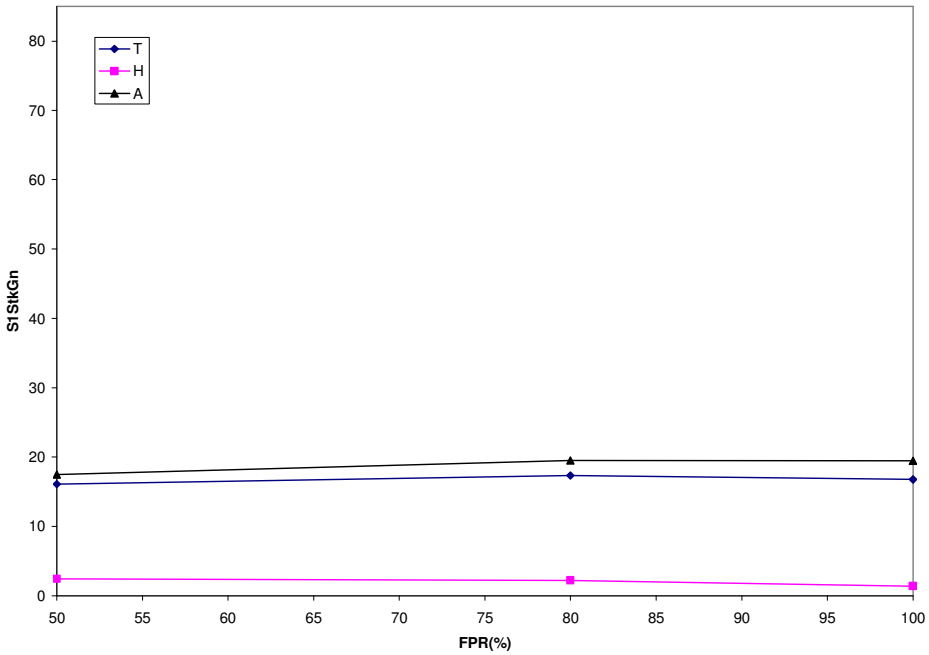

Figure 5.18 S1Sellers' Performance Trends with FPR in Two-item Situation

CHAPTER 6

CONCLUSION

Buyers equipped with the proposed model significantly gain more than those with the competing models in all the testing scenarios even in the presence of noise at three different levels and incomplete information at three different levels. Buyers provided with the proposed trust model will gain more in the E-Marketplace than with any of the competing models. They are more satisfied with the proposed model and more likely to stay in the E-Marketplace.

As to the sellers, the proposed model always favors the trustworthy sellers and penalizes the untrustworthy ones. This is consistent with the expected behavior in the experiment. If an E-Marketplace provides a trust evaluation system with the proposed model, the trustworthy sellers gain the most and they are satisfied by providing satisfactory service, gaining more and more likely to stay in the E-Marketplace. However, the untrustworthy sellers gains the least, they are more likely to leave.

In summary, the proposed model is a better model than the competing models; it leads to increased buyers' gain, it favors trustworthy sellers and punishes the untrustworthy ones, and it is robust in the presence of noise and incomplete information in the E-Marketplace. By satisfying both buyers and trustworthy sellers, the proposed model can help to build and retain a flourishing E-Marketplace.

The trust model alone is not sufficient to maintain the order of an E-Marketplace. Accompanied by the institution enforcement, the trust model in the E-Marketplace can generate the synergy to deter cheaters and strategic traders so as to keep the E-Marketplace healthy.

The trust value from the proposed model may be only an approximation of the trust. However, taking the Scientific Realism stance, one may get closer to the truth of trust though, at present, one may have approximate truth about the trust in the E-Marketplace.

As to some other kind of strategic traders, they may abuse the established reputation and then change their pseudonyms and play the circle of building reputation, abusing the reputation and changing the pseudonyms time and again. But as new comers, this kind of strategic traders always have to pay the due of building reputation which is time consuming if the proposed model is in effect. This model hinders the strategic traders to some extent.

CHAPTER 7

LIMITATIONS AND FUTURE RESEARCH

There are some limitations we need to address here. As mentioned, when the direct reputation component is calculated in section 3.1.4, the average is taken for simplicity, so is the temporal-effect factor and price-volume factor of the ratings in section 3.2.1. Better weighting schemes are expected. And also in section 3.1.2, a subjective weight scheme is adopted to weigh the positive ratings and negative ones, which calls for a better solution.

In the simulation, the trust values of each seller are calculated in each tick, which brings on too much overhead in computation. Better solutions are expected to reduce the computational complexity of the trust values.

In current simulation, there is no cost for the S2Sellers to use shills, that is, the shills just post positive feedback for the shilled sellers free of charge, though in a real E-Marketplace the cost of using shill can be very cheap.

Besides the above-mentioned points, more work can be done to push this research work further.

7.1 Adding More Dynamics in the E-Marketplace

Even though there are certain dynamics in the simulation such as the ASVs of a seller drawn from certain normal distribution according to its set status, buyers generate the purchase demand based on a certain normal distribution. S1Sellers and S2Sellers

switch their behaviors based on the self-calculated reputation values and more experiments can be conducted to test the robustness of the model in various other situations. For example, more dynamics can be introduced into the mini E-Marketplace which allows old buyers and sellers to leave the E-Marketplace and new buyers and sellers to enter the E-Marketplace. Adaptive Sellers, who learn their strategies and change their behaviors according to the frequency of being selected by buyers, can be adopted into the E-Marketplace.

In the current simulation, there is only one trust model used in each simulation plan, that is, there is only one kind of trust model in an E-Marketplace. Further research can be done to study the performance of buyers equipped with different trust models in the same E-Marketplace.

7.2 Taking Population Ecology Approach

Population Ecology Approach can be taken to study how a population of buyers using different trust models evolves. After each tick, some buyers are eliminated through selection. After certain number of ticks, if the trust model is superior, the population of the buyers that are using it should gradually expand and the population of the buyers using a secondary trust model should gradually shrink. This can be another way to compare the performance of two models.

7.3 Taking into Account Reputation of Buyers

The current proposed model does not take into account of the reputation of the witness buyers in the calculation of a trust value of a seller. The reputable witness

buyers' feedback should carry more weight in the trust estimation of a designated seller. Further research is needed to devise the way to do so.

7.4 Finding More Constructs to Enrich the Proposed Model

In this research, the factors of positive/negative impact effect, temporal effect, and price volume effect are integrated into the constructs of DR and WR of the trust model. To find more constructs and factors to enrich the trust model can be the focus of future work.

APPENDIX A

PROOF OF INEQUATIONS

$$GS_{a_m a_n}(t) = (LSV - ASV) + m \cdot LSV > 0$$
$$=> (1+m) \cdot LSV - ASV > 0$$
$$=> ASV < (1+m) \cdot LSV$$
$$=> (1+g) \cdot LSV + 2\sigma < (1+m) \cdot LSV$$
$$=> \sigma < \frac{(m-g) \cdot LSV}{2}$$
$$\sigma < \frac{(m-g) \cdot LSV}{2}$$
$$\because \sigma \geq 0$$
$$\therefore m \geq g$$

$$Satisfactory \quad Service'ASV \quad Range \quad [(1+g) \cdot LSV - 2\sigma, (1+g) \cdot LSV + 2\sigma]$$
$$Unsatisfactory \quad Service'ASV \quad Range \quad [(1-g) \cdot LSV - 2\sigma, (1-g) \cdot LSV + 2\sigma]$$
$$Among\, these \quad ASVs \quad the \quad smallest \quad is\, (1-g) \cdot LSV - 2\sigma \quad ,the \quad biggest \quad is\, (1+g) \cdot LSV + 2\sigma.$$
$$\because \quad a \quad buyer's \quad rating \quad on \quad a \quad seller \quad is \quad in \quad the \quad range \quad of \quad [-1,+1].$$
$$\therefore \begin{cases} (1-g) \cdot LSV - 2\sigma \geq -1 \\ (1+g) \cdot LSV + 2\sigma \leq +1 \end{cases}$$
$$i.e. \quad \sigma \leq \frac{(1-g) \cdot LSV}{2}$$

APPENDIX B

ACROSS MODEL PERFORMANCE COMPARISON TABLES

Abbreviation	Meaning
T	The traditional model
H	Huynh's model
A	The Adaptive Reputation-based Trust Model, the proposed model
r0	Run 0 or Round 0
Avg.	The CTG of the corresponding buyers or sellers with the corresponding model
Std.	The standard deviation of the corresponding OTG sequence of the corresponding buyers or sellers with the corresponding model
P_T	The p-values of the corresponding sequences' mean-difference testing with the traditional model
P_H	The p-values of the corresponding sequences' mean-difference testing with Huynh's model
Two-item Ns=p2	The performance table at Noise level of 0.2 in two-item situation
One-item Base Situation	The performance table in the base scenario in two-item situation
BuyerTkGn	The average of the Buyers' tick gains of the last 100 ticks
1GSellerTkGn	The average of the 1GSellers' tick gains of the last 100 ticks
0.8GSellerTkGn	The average of the 0.8GSellers' tick gains of the last 100 ticks
0.5GSellerTkGn	The average of the 0.5GSellers' tick gains of the last 100 ticks
S1SellerTkGn	The average of the S1Sellers' tick gains of the last 100 ticks
S2SellerTkGn	The average of the S2Sellers' tick gains of the last 100 ticks

1-item Base Situation

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	51.7	58.439	72.437	17.45	30.68	25.83	5.94	3.444	6.56	0.36	5.113	1.654	12.28	2.647	13.62	33.45	20.84	1.06
r1	52.8	66.46	70.994	19.58	35.84	23.43	3.62	0.662	8.375	0.78	1.781	1.752	12.59	0.921	15.63	31.91	15.62	1.102
r2	49.5	65.12	69.735	16.95	34.89	23.98	6.84	1.213	7.45	1.66	2.127	2.566	12.48	0.801	14.5	31.9	15.17	1.088
r3	50.4	66.835	71.338	16.97	35.46	24.5	6.63	1.281	7.289	0.99	2.046	1.946	12.12	0.857	14.46	33.12	13.78	0.72
r4	51.2	66.1	71.974	18.96	35.14	25.15	4.91	1.255	6.18	0.71	0.672	2.652	12.28	0.877	13.53	32.3	16.26	0.821
r5	52.4	65.619	72.458	19.32	35.16	25.31	4.53	0.891	5.27	0.28	2.419	1.913	11.84	0.676	14.68	31.9	15.54	0.676
r6	52.1	66.705	71.894	19.43	35.71	24.74	4.96	0.878	6.516	0.24	1.154	1.92	10.97	0.468	14.24	32.52	15.29	0.895
r7	51.6	65.485	71.843	19.07	34.82	26.74	5.34	1.342	4.771	0.45	2.184	1.797	11.33	1.136	13.73	32.71	15.57	1.653
r8	50.8	59.909	72.266	18.69	31.8	25.35	5.73	2.361	6.413	0.76	5.23	1.693	11.28	2.312	13.23	32.54	18.19	0.854
r9	50.4	64.633	73.461	17.15	34.59	25.44	6.53	1.152	5.293	0.79	2.306	1.498	13.65	1.327	14.09	32.07	16.55	0.776
Avg.	**51.3**	**64.53**	**71.84**	**18.36**	**34.41**	**25.05**	**5.5**	**1.448**	**6.412**	**0.7**	**2.503**	**1.939**	**12.08**	**1.202**	**14.17**	**32.44**	**16.28**	**0.964**
Std.	*20.4*	*13.55*	*11.66*	*4.58*	*5.241*	*4.53*	*5.81*	*3.249*	*6.475*	*2.41*	*5.468*	*4.097*	*9.762*	*2.657*	*11.33*	*20.05*	*13*	*3.065*
									Paired t-test (2 tail)									
P_T		2E-07	2E-12		4E-10	1E-07		8E-07	0.102		0.006	5E-06		1E-10	4E-05		4E-10	3E-17
P_H			8E-05			4E-07			2E-06			0.33			1E-10			1E-09

1-item Ns=p2

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	52.4	48.885	71.257	20.22	0.641	24.72	4.49	0.552	6.375	0.29	1.994	2.106	12.04	0.914	15.06	31.76	68.18	1.651
r1	49.2	63.281	72.644	15.97	33.68	26.25	7.99	2.309	6.162	0.58	2.822	1.874	13.7	1.772	13.78	33.9	17.42	0.573
r2	50.3	66.054	70.882	17.34	34.83	24.19	5.65	1.014	7.024	0.7	1.727	2.732	13.64	1.234	13.94	31.69	14.46	0.554
r3	48.4	61.752	71.311	15.85	33.22	24.95	9.02	1.366	5.43	2.26	3.326	1.435	11.62	1.584	15.58	33.14	19.01	1.557
r4	49.6	61.974	72.098	16.57	32.56	24.47	7.34	2.066	6.949	0.8	3.57	1.352	12.67	1.768	14.49	33.33	18.37	0.947
r5	51.2	67.33	72.353	18.94	35.34	23.14	4.82	1.159	7.457	0.53	1.712	1.729	11.66	0.747	14.93	33.11	14.02	0.705
r6	52.5	52.394	70.138	20.35	26.57	23.89	5.21	3.469	8.013	0.31	9.212	1.811	10.32	3.534	15.47	31.51	25.02	0.878
r7	51	63.668	71.708	17.43	34.06	24	6.63	1.815	6.703	1.29	2.756	2.288	12.47	1.228	14.85	31.71	17.01	0.979
r8	52	42.893	71.887	19.02	21.57	25.47	5.26	7.269	5.185	0.7	10.75	1.76	13.04	5.91	14.82	29.79	31.41	0.682
r9	51	57.562	71.364	18.32	29.56	23.52	5.69	4.272	7.822	0.93	6.33	1.866	11.89	2.818	14.76	32.75	20.02	1.226
Avg.	**50.7**	**58.579**	**71.564**	**18**	**28.2**	**24.46**	**6.21**	**2.529**	**6.712**	**0.84**	**4.42**	**1.895**	**12.31**	**2.151**	**14.77**	**32.27**	**24.49**	**0.975**
Std.	*19.5*	*19.98*	*12.59*	*4.76*	*6.167*	*4.76*	*6.48*	*4.151*	*6.427*	*2.5*	*6.97*	*4.104*	*10.17*	*4.236*	*11.64*	*19.37*	*20.4*	*3.238*
									Paired t-test (2 tail)									
P_T		0.0221	4E-11		0.022	6E-06		0.002	0.465		0.008	0.002		4E-08	7E-04		0.174	4E-14
P_H			0.0005			0.302			4E-04			0.042			1E-09			0.001

1-item Ns=p5

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	73.4	86.944	104.54	20.69	47.77	32.04	8.16	1.987	9.994	0.89	4.12	3.373	19.09	1.823	20.68	49.32	29.54	1.559
r1	77.7	66.55	103.24	21.99	4.201	30.96	4.95	6.728	10.51	0.56	10.14	3.286	17.54	4.125	21.82	48.71	79.89	1.827
r2	73.6	71.415	105.67	21.79	0.773	30.66	5.06	0.688	9.562	0.31	3.145	0.627	17.94	0.573	24.36	52.77	95.02	0.745
r3	73.7	72.798	106.16	20.93	2.744	31.26	7.2	3.209	8.026	2.44	5.227	2.831	16.35	2.801	23.6	52.06	86.52	1.419
r4	73.9	86.114	106.97	23.32	48.11	31.65	6.15	1.113	7.023	0.4	2.732	1.323	19.16	1.287	21.86	48.37	32.34	2.872
r5	74.1	82.403	105.63	21.39	45.32	29.66	4.8	3.112	10.41	0.41	4.101	1.877	19.64	1.535	22.41	50.67	34.72	1.201
r6	74.4	72.278	103.28	21.64	1.146	30.86	6.6	1.416	7.774	0.98	3.263	3.85	17.66	0.988	23.85	49.22	92.04	1.518
r7	74.4	72.472	106.48	22.21	0.689	31.96	6.52	1.478	8.665	1.09	3.19	1.668	16.42	1.614	21.07	50.65	92.31	1.914
r8	73.6	82.517	103.57	22.66	46.63	28.96	6.97	2.594	9.155	0.72	2.895	2.254	17.47	0.936	23.83	48.83	35.01	2.825
r9	72.8	70.997	103.29	21.24	3.698	29.61	5.96	2.556	10.91	1.22	3.897	4.049	17.55	1.879	21.77	52.34	88.35	1.737
Avg.	**74.2**	**76.449**	**104.88**	**21.78**	**20.11**	**30.76**	**6.24**	**2.488**	**9.202**	**0.9**	**4.271**	**2.514**	**17.88**	**1.756**	**22.52**	**50.29**	**66.57**	**1.762**
Std.	*31.2*	*46.11*	*15.34*	*6.88*	*4.907*	*7.23*	*6.73*	*4.793*	*8.685*	*3.09*	*8.564*	*5.297*	*11.87*	*3.332*	*12.75*	*32.59*	*45.8*	*5.055*
									Paired t-test (2 tail)									
P_T		0.3874	8E-12		0.823	6E-09		6E-04	0.001		0.001	9E-04		3E-10	3E-05		0.103	1E-13
P_H			4E-07			0.182			3E-07			0.025			8E-11			7E-05

1-item FPR=P8

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	46.7	63.948	72.12	18.64	34.97	25.72	6.29	1.021	6.232	0.46	1.784	2.407	11.56	0.617	13.63	37.47	18.82	1.054
r1	49.8	63.18	72.228	20.3	34.78	25.52	4.51	0.951	4.846	0.44	1.616	2.412	10.71	0.634	14.31	35.53	20.12	1.965
r2	46.8	56.364	71.402	18.3	30.85	24.65	4.67	3.063	6.776	0.5	3.976	2.545	12.54	1.748	12.89	36.52	23.32	1.058
r3	45.8	47.75	73.222	18.91	26.65	27.17	6.05	4.682	3.901	0.4	6.967	1.482	11.6	2.959	13.64	37.45	31.25	0.841
r4	46.7	62.715	72.826	18.71	35.04	25.54	5.43	0.925	4.847	0.15	0.789	2.224	12.11	0.746	14.03	37.22	20.09	0.843
r5	45.9	50.959	72.016	17.28	27.12	26	7.8	3.533	4.622	0.69	6.794	2.262	12.67	3.351	14.71	35.93	28.55	0.698
r6	47.1	52.786	72.604	16.84	27.87	26.05	6.7	4.157	4.727	0.26	6.911	1.85	12.07	3.586	13.83	37.25	24.89	1.149
r7	45.2	49.122	71.942	16.42	25.77	24.45	6.45	5.644	6.265	0.74	7.292	2.051	13.47	3.554	14.52	38.26	29.15	1.303
r8	45.2	51.91	71.189	17.66	27.83	24.72	6.5	4.078	6.478	0.97	6.983	1.723	11.73	3.166	14.47	37.71	25.83	1.221
r9	45.9	40.548	71.269	16.31	1.764	25.96	6.58	2.481	5.88	0.54	4.093	2.756	11.45	2.404	13.53	39.83	69.27	1.162
Avg.	**46.5**	**53.928**	**72.082**	**17.94**	**27.27**	**25.58**	**6.1**	**3.054**	**5.457**	**0.52**	**4.721**	**2.171**	**11.99**	**2.277**	**13.96**	**37.32**	**29.13**	**1.129**
Std.	*19.4*	*19.83*	*11.97*	*4.53*	*6.275*	*4.45*	*6.32*	*4.769*	*5.882*	*1.99*	*7.418*	*4.541*	*9.323*	*3.815*	*10.84*	*20.47*	*15.6*	*3.488*
									Paired t-test (2 tail)									
P_T		0.0077	5E-13		0.009	3E-08		1E-04	0.207		5E-04	2E-06		3E-10	6E-05		0.094	2E-14
P_H			3E-05			0.601			0.003			0.02			2E-10			2E-04

1-item FPR=p5

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	34	29.752	74.896	18	0.526	33.86	4.83	0.946	1.91	0.57	1.448	2.129	12.66	0.837	5.087	51.06	87.66	3.287
r1	31.5	43.562	73.507	19.22	27.01	29.9	2.71	3.766	2.916	0.56	4.333	1.924	12.12	2.506	10.39	55.21	40.1	2.646
r2	30.6	25.108	75.201	17.13	1.849	31.99	7.01	2.418	2.838	0.38	4.385	1.613	11.01	3.264	6.918	53.21	82.3	0.758
r3	36.4	47.867	73.969	17.14	30.77	31.62	6.92	1.616	6.431	0.61	1.928	1.385	12.67	0.837	5.928	46.53	37.24	0.924
r4	37.5	27.944	75.206	19	0.591	31.8	4.97	0.78	1.929	0.43	1.863	1.576	11.07	0.846	8.59	47.38	88.29	1.215
r5	33.6	51.116	73.694	17.05	31.52	31.99	5.79	0.876	5.396	0.51	1.626	2.293	11.91	1.241	6.151	51.43	33.92	0.783
r6	33.3	27.065	73.117	17.2	0.347	29.43	6.13	1.255	6.59	0.48	1.422	1.791	10.74	0.592	8.123	52.36	89.52	1.149
r7	31.4	22.654	73.698	16.98	2.768	29.47	5.7	2.406	4.745	0.19	5.634	1.16	11.47	2.803	10.62	54.82	84.27	0.845
r8	35.1	27.356	74.637	17.75	1.224	33.22	5.19	1.54	3.121	0.8	2.472	2.01	11.19	0.813	5.686	49.82	86.4	1.131
r9	30.3	27.603	73.774	15.87	0.745	32.06	7.58	0.939	3.609	0.9	1.084	1.66	13.22	0.424	7.924	52.74	89.77	1.532
Avg.	**33.4**	**33.003**	**74.17**	**17.53**	**9.736**	**31.53**	**5.68**	**1.654**	**3.948**	**0.54**	**2.619**	**1.754**	**11.81**	**1.416**	**7.542**	**51.46**	**71.95**	**1.427**
Std.	*18.1*	*43.38*	*9.479*	*4.62*	*3.044*	*4.27*	*5.9*	*3.627*	*5.016*	*2.17*	*5.443*	*3.898*	*10.1*	*2.928*	*7.738*	*20.7*	*40.2*	*3.718*
									Paired t-test (2 tail)									
P_T		0.9142	1E-12		0.108	2E-09		1E-04	0.011		0.004	8E-07		4E-09	2E-04		0.025	1E-12
P_H			6E-07			9E-04			0.006			0.155			1E-06			7E-06

2-item Base Situation

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	74	92.133	102.25	26.41	49.7	35.89	7.83	1.861	9.816	1.43	2.197	2.787	17.18	1.058	19.75	44.9	25.24	1.695
r1	66.9	89.918	102.1	22.57	48.78	35.7	11.9	1.999	10.49	4.19	3.187	3.477	17.5	1.217	18.98	47.29	26.54	0.887
r2	74.1	91.12	101.05	27.49	50.18	35.62	6.33	1.741	12.67	1.14	1.694	2.807	16.26	1.238	17.83	45.86	25.64	1.637
r3	73.5	92.833	103.06	27.22	50.18	36.39	6.99	1.117	9.151	0.07	2.274	2.367	17.24	1.537	20.56	47.82	25.35	1.775
r4	73.5	92.091	102.23	25.94	49.89	36.65	8.36	1.179	9.756	0.34	2.91	3.492	17.11	0.876	18.67	45.91	24.75	0.889
r5	73.2	89.316	101.56	25.69	48.17	33.71	8.14	2.622	11.1	0.79	2.405	3.167	16.93	2.027	20.62	45.83	26.64	1.03
r6	73.6	89.718	103.78	27.04	48.32	36.11	7.47	1.783	9.216	0.54	3.888	1.693	16.46	1.422	19.12	45.61	26	1.217
r7	72.1	91.448	102.13	25.87	49.98	36.01	8.27	2.069	10.61	1.61	2.159	2.062	17.2	1.037	19.85	46.01	25.06	1.084
r8	73.9	84.797	101.69	27.08	45.77	34.96	7.68	3.17	9.187	0.5	5.63	3.016	16.14	2.299	20.08	44.64	28.92	1.653
r9	73.7	92.934	102.27	27.34	49.96	36.97	6.75	1.193	9.047	0.91	1.366	3.157	15.8	1.434	19.14	46.56	24.49	0.787
Avg.	**72.9**	**90.631**	**102.21**	**26.26**	**49.09**	**35.8**	**7.97**	**1.873**	**10.1**	**1.15**	**2.771**	**2.803**	**16.78**	**1.415**	**19.46**	**46.04**	**25.86**	**1.265**
Std.	*29.3*	*18.63*	*16.87*	*7.21*	*7.088*	*7.03*	*7.73*	*4.201*	*8.701*	*3.06*	*6.236*	*5.542*	*14.26*	*3.357*	*15.83*	*28.25*	*19.9*	*4.334*
									Paired t-test (2 tail)									
P_T		2E-08	2E-11		4E-11	1E-08		6E-07	0.006		0.017	0.001		9E-13	6E-06		9E-11	7E-16
P_H			8E-08			4E-11			5E-09			0.944			5E-14			3E-13

2-item Ns=p2

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	74.3	93.279	103.44	27.79	50.64	36.05	7.64	1.501	8.536	0.47	1.394	1.86	17.53	0.796	20.62	44.13	24.58	1.679
r1	72.1	75.883	102	26.46	42.19	34.91	7.33	4.827	9.678	0.94	7.555	2.052	16.73	3.378	21.62	47.9	37.8	1.376
r2	72.2	79.09	101.99	26.61	41.25	35.65	6.93	5.453	8.835	0.44	7.104	1.967	17.71	4.933	21.83	47.23	33.79	1.343
r3	74.4	92.726	103.85	27.44	50.4	35.91	7.28	1.308	9.835	0.24	2.468	1.226	17.2	1.219	20.77	46.33	25.18	1.71
r4	74.6	83.731	102.53	26.6	43.93	35.47	7.54	5.288	10.52	1.02	5.892	2.536	17.14	3.794	19.64	44.26	29.06	1.003
r5	74	84.085	103.17	27.78	44.41	37.55	6.87	3.835	8.032	0.64	5.064	2.894	16.84	3.148	17.94	44.71	30.65	1.591
r6	73	89.893	100.61	27.6	48.32	35.9	8	1.998	9.854	0.65	2.86	2.662	17.59	0.988	20.38	43.76	27.07	1.725
r7	72.3	86.424	102.65	25.94	46.57	35.68	8.45	3.257	10.24	0.85	5.55	2.404	17.5	2.389	20.07	46.18	27.56	0.703
r8	73.2	90.512	90.512	27.37	49.13	49.13	7.12	1.383	1.383	0.53	2.376	2.376	17.14	1.106	1.106	44.87	26.08	26.08
r9	72.6	89.189	102.57	25.49	48.87	36.95	9.22	1.828	8.662	0.81	2.069	2.164	17.13	1.256	19.39	45.25	28.16	1.642
Avg.	**73.3**	**86.481**	**101.33**	**26.91**	**46.57**	**37.32**	**7.64**	**3.068**	**8.557**	**0.66**	**4.233**	**2.214**	**17.25**	**2.301**	**18.34**	**45.46**	**28.99**	**3.885**
Std.	*27.4*	*22.51*	*17.61*	*7.08*	*9.608*	*7.2*	*7.4*	*5.828*	*8.318*	*2.57*	*8.221*	*5.007*	*13.79*	*4.663*	*14.54*	*27.34*	*22.8*	*6.335*
									Paired t-test (2 tail)									
P_T		3E-05	3E-09		1E-08	2E-05		6E-05	0.282		5E-04	5E-07		2E-10	0.587		8E-08	6E-08
P_H			0.0001			1E-04			8E-05			0.018			1E-05			2E-05

2-item Ns=p5

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	73.4	86.944	104.54	20.69	47.77	32.04	8.16	1.987	9.994	0.89	4.12	3.373	19.09	1.823	20.68	49.32	29.54	1.559
r1	77.7	66.55	103.24	21.99	4.201	30.96	4.95	6.728	10.51	0.56	10.14	3.286	17.54	4.125	21.82	48.71	79.89	1.827
r2	73.6	71.415	105.67	21.79	0.773	30.66	5.06	0.688	9.562	0.31	3.145	0.627	17.94	0.573	24.36	52.77	95.02	0.745
r3	73.7	72.798	106.16	20.93	2.744	31.26	7.2	3.209	8.026	2.44	5.227	2.831	16.35	2.801	23.6	52.06	86.52	1.419
r4	73.9	86.114	106.97	23.32	48.11	31.65	6.15	1.113	7.023	0.4	2.732	1.323	19.16	1.287	21.86	48.37	32.34	2.872
r5	74.1	82.403	105.63	21.39	45.32	29.66	4.8	3.112	10.41	0.41	4.101	1.877	19.64	1.535	22.41	50.67	34.72	1.201
r6	74.4	72.278	103.28	21.64	1.146	30.86	6.6	1.416	7.774	0.98	3.263	3.85	17.66	0.988	23.85	49.22	92.04	1.518
r7	74.4	72.472	106.48	22.21	0.689	31.96	6.52	1.478	8.665	1.09	3.19	1.668	16.42	1.614	21.07	50.65	92.31	1.914
r8	73.6	82.517	103.57	22.66	46.63	28.96	6.97	2.594	9.155	0.72	2.895	2.254	17.47	0.936	23.83	48.83	35.01	2.825
r9	72.8	70.997	103.29	21.24	3.698	29.61	5.96	2.556	10.91	1.22	3.897	4.049	17.55	1.879	21.77	52.34	88.35	1.737
Avg.	**74.2**	**76.449**	**104.88**	**21.78**	**20.11**	**30.76**	**6.24**	**2.488**	**9.202**	**0.9**	**4.271**	**2.514**	**17.88**	**1.756**	**22.52**	**50.29**	**66.57**	**1.762**
Std.	*31.2*	*46.11*	*15.34*	*6.88*	*4.907*	*7.23*	*6.73*	*4.793*	*8.685*	*3.09*	*8.564*	*5.297*	*11.87*	*3.332*	*12.75*	*32.59*	*45.8*	*5.055*
									Paired t-test (2 tail)									
P_T		0.3874	8E-12		0.823	6E-09		6E-04	0.001		0.001	9E-04		3E-10	3E-05		0.103	1E-13
P_H			4E-07			0.182			3E-07			0.025			8E-11			7E-05

2-item FPR=P8

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	66.5	84.885	104.7	27.87	47.5	36.48	7.64	2.059	10.88	0.62	2.683	2.201	16.13	1.957	16.91	52.74	33.11	1.01
r1	63.6	79.096	100.57	28.07	43.8	35.2	7.17	4.571	8.719	0.51	6.071	3.216	16.62	2.489	22.24	55.21	35.61	1.688
r2	61.7	81.858	101.4	23.6	46.25	34.17	9.96	2.423	9.538	1.72	3.111	2.953	17.08	1.655	20.99	56.72	36.32	2.563
r3	67.6	83.138	104.15	25.91	47.89	37.37	7.28	1.803	8.955	0.96	2.287	2.171	19	0.991	19.07	52.09	37.19	1.578
r4	66.9	57.413	103.6	26.32	0.963	35.84	6.14	1.401	10.4	0.56	2.015	2.289	17	0.971	18.59	54.54	108.9	0.974
r5	63.6	79.298	102.22	22	46.75	36.9	9.64	0.917	7.861	4.27	2.84	2.44	18.37	1.077	20.58	52.36	40.31	1.194
r6	66.1	72.027	101.75	27.55	39.01	36.51	7.5	5.196	8.45	0.76	10.64	3.739	15.55	4.444	18.75	53.32	39.81	1.931
r7	65.4	83.205	104.05	27.41	48.24	36.71	7.71	1.58	8.342	0.65	1.3	3.068	16.68	0.95	18.75	53.3	36.47	0.842
r8	64.4	79.776	102.02	24.98	41.89	35.99	8.9	3.953	9.224	0.86	7.095	1.963	17.22	3.912	19.82	53.44	33.96	1.571
r9	64.6	72.501	100.38	25.46	40.88	35.42	6.6	4.951	11.54	1.01	6.502	2.736	19.75	3.626	19.6	53.44	42.91	1.684
Avg.	**65**	**77.32**	**102.48**	**25.92**	**40.32**	**36.06**	**7.85**	**2.885**	**9.392**	**1.19**	**4.455**	**2.678**	**17.34**	**2.207**	**19.53**	**53.72**	**44.46**	**1.503**
Std.	*28.8*	*28.84*	*17.64*	*7.1*	*8.448*	*7.19*	*7.44*	*5.064*	*8.812*	*3.45*	*8.423*	*5.465*	*13.38*	*4.239*	*16.14*	*28.93*	*31.1*	*4.881*
									Paired t-test (2 tail)									
P_T		0.0018	1E-14		0.012	9E-08		7E-05	0.045		0.014	0.007		2E-09	0.004		0.228	3E-16
P_H			4E-06			0.364			1E-06			0.072			4E-10			2E-04

2-item FPR=p5

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A	T	H	A
r0	45.9	50.96	105.71	25.07	39.08	39.51	8.48	2.239	4.378	0.25	2.13	1.874	17.53	2.133	19.29	74.38	75.65	1.432
r1	43.7	57.881	106.11	25.44	38.52	44.72	8.65	3.39	4.584	0.54	4.957	2.003	14.69	2.849	10.51	78.16	64.04	3.712
r2	51.5	59.062	102.92	27.19	40.47	38.53	6.26	2.543	3.238	0.61	4.787	2.416	14.97	1.248	21.21	70.65	63.51	3.311
r3	52.5	61.036	108.07	27.12	42.33	40.64	7.2	1.533	6.359	0.42	2.397	1.845	16.78	1.334	14.67	68.72	64.67	1.708
r4	45.1	59.069	104.45	22.13	42.07	39.01	10.7	1.074	5.365	3.59	2.256	2.853	17.04	0.67	19.02	72.12	66.56	0.991
r5	46.9	30.1	103.04	24.17	0.795	37.93	9.79	1.19	7.325	0.9	1.57	2.621	15.08	0.72	18.47	73.14	136.8	1.806
r6	48.4	59.986	102.86	25.19	42.11	40.54	6.28	1.013	5.905	0.55	2.293	1.531	15.67	0.743	16.1	74.69	64.99	4.196
r7	50.7	56.61	101.6	26.44	39.49	42.15	6	2.557	4.01	0.35	4.226	1.756	17.33	1.827	18.78	70.64	67.04	3.466
r8	46.9	18.885	104.93	22.59	9.67	38.45	9.86	15.27	5.243	2.92	18.13	2.488	16.5	12.1	18.84	71.32	96.54	0.632
r9	45.8	30.813	103.14	25.86	0.807	39.71	8.38	0.817	6.987	0.86	2.132	1.614	15.25	0.628	17.9	74.88	136.2	2.024
Avg.	**47.7**	**48.44**	**104.28**	**25.12**	**29.53**	**40.12**	**8.16**	**3.163**	**5.34**	**1.1**	**4.488**	**2.1**	**16.08**	**2.425**	**17.48**	**72.87**	**83.6**	**2.328**
Std.	*25.3*	*36.69*	*17.17*	*6.8*	*6.483*	*7.08*	*7.94*	*4.874*	*6.385*	*3.21*	*7.2*	*4.906*	*12.33*	*4.024*	*15.6*	*28.52*	*35.6*	*5.8*
									Paired t-test (2 tail)									
P_T		0.8856	3E-12		0.447	4E-09		0.004	5E-04		0.041	0.006		6E-07	0.16		0.276	2E-14
P_H			1E-06			0.084			0.181			0.153			2E-06			1E-05

APPENDIX C

WITHIN MODEL PERFORMANCE COMPARISON TABLES

Abbreviation	Meaning
T	The traditional model
H	Huynh's model
A	The Adaptive Reputation-based Trust Model, the proposed model
r0	Run 0 or Round 0
Avg.	The CTG of the corresponding buyers or sellers with the corresponding model
Std.	The standard deviation of the corresponding OTG sequence of the corresponding buyers or sellers with the corresponding model
P_{Base}	The p-values of the corresponding sequences' mean-difference testing in the Base scenario with the corresponding model
P_{FpP8}	The p-values of the corresponding sequences' mean-difference testing at FPR of 0.8 with the corresponding model
Two-item traditional model FPR	The performance table for the traditional model at different FPR levels in two-item situation
BuyerTkGn	The average of the Buyers' tick gains of the last 100 ticks
1GSellerTkGn	The average of the 1GSellers' tick gains of the last 100 ticks
0.8GSellerTkGn	The average of the 0.8GSellers' tick gains of the last 100 ticks
0.5GSellerTkGn	The average of the 0.5GSellers' tick gains of the last 100 ticks
S1SellerTkGn	The average of the S1Sellers' tick gains of the last 100 ticks
S2SellerTkGn	The average of the S2Sellers' tick gains of the last 100 ticks
tBase	Traditional model in base scenario
hNsP2	Huynh's model at noise level of 0.2
aFpP8	Adaptive reputation-based trust model at FPR lever of 80%

1-item traditioanl Model Noise

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5
r0	51.69	52.36	51.6	17.45	20.2	15.14	5.939	4.49	4.788	0.36	0.288	0.78	12.3	12.04	12.96	33.45	31.8	35.89
r1	52.8	49.15	52.08	19.58	16	14.75	3.617	7.99	5.802	0.78	0.575	0.2	12.6	13.7	14.03	31.91	33.9	34.42
r2	49.49	50.31	50	16.95	17.3	13.89	6.837	5.65	6.039	1.66	0.696	1.095	12.5	13.64	13.01	31.9	31.7	35.28
r3	50.43	48.37	51.96	16.97	15.9	15.51	6.633	9.02	3.676	0.99	2.26	0.744	12.1	11.62	12.46	33.12	33.1	35.91
r4	51.15	49.61	51.99	18.96	16.6	14.3	4.907	7.34	4.596	0.71	0.796	0.257	12.3	12.67	13.42	32.3	33.3	35.74
r5	52.44	51.24	53.23	19.32	18.9	15.45	4.53	4.82	3.488	0.28	0.53	0.109	11.8	11.66	13.15	31.9	33.1	34.88
r6	52.09	52.5	51.77	19.43	20.3	15.75	4.961	5.21	4.424	0.24	0.312	0.037	11	10.32	13.39	32.52	31.5	34.83
r7	51.65	50.99	52.46	19.07	17.4	13.45	5.344	6.63	6.341	0.45	1.295	0.793	11.3	12.47	12.59	32.71	31.7	34.9
r8	50.8	51.99	52.34	18.69	19	16.14	5.726	5.26	3.587	0.76	0.696	0.203	11.3	13.04	12.2	32.54	29.8	35.33
r9	50.37	50.98	51.17	17.15	18.3	13.23	6.531	5.69	7.8	0.79	0.934	2.195	13.7	11.89	12.83	32.07	32.7	33.35
Avg.	**51.29**	**50.75**	**51.86**	**18.36**	**18**	**14.76**	**5.503**	**6.21**	**5.054**	**0.7**	**0.838**	**0.641**	**12.1**	**12.31**	**13.01**	**32.44**	**32.3**	**35.05**
Std.	*20.4*	*19.46*	*21.71*	*4.576*	*4.76*	*4.512*	*5.81*	*6.48*	*5.568*	*2.41*	*2.5*	*2.04*	*9.76*	*10.17*	*9.556*	*20.05*	*19.4*	*22*
P_{Base}		0.302	0.039		0.56	9E-06		0.26	0.389		0.488	0.769		0.528	0.007		0.71	4E-07
P_{NsP2}			0.053			1E-04			0.106			0.429			0.075			3E-04

1-item traditonal Model FPR

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5
r0	51.69	46.74	34.04	17.45	18.6	18	5.939	6.29	4.828	0.36	0.464	0.572	12.3	11.56	12.66	33.45	37.5	51.06
r1	52.8	49.8	31.46	19.58	20.3	19.22	3.617	4.51	2.715	0.78	0.445	0.555	12.6	10.71	12.12	31.91	35.5	55.21
r2	49.49	46.79	30.58	16.95	18.3	17.13	6.837	4.67	7.009	1.66	0.498	0.379	12.5	12.54	11.01	31.9	36.5	53.21
r3	50.43	45.84	36.38	16.97	18.9	17.14	6.633	6.05	6.923	0.99	0.4	0.613	12.1	11.6	12.67	33.12	37.4	46.53
r4	51.15	46.69	37.47	18.96	18.7	19	4.907	5.43	4.969	0.71	0.154	0.426	12.3	12.11	11.07	32.3	37.2	47.38
r5	52.44	45.92	33.61	19.32	17.3	17.05	4.53	7.8	5.788	0.28	0.695	0.509	11.8	12.67	11.91	31.9	35.9	51.43
r6	52.09	47.09	33.29	19.43	16.8	17.2	4.961	6.7	6.126	0.24	0.262	0.482	11	12.07	10.74	32.52	37.3	52.36
r7	51.65	45.17	31.38	19.07	16.4	16.98	5.344	6.45	5.698	0.45	0.743	0.189	11.3	13.47	11.47	32.71	38.3	54.82
r8	50.8	45.24	35.06	18.69	17.7	17.75	5.726	6.5	5.186	0.76	0.973	0.8	11.3	11.73	11.19	32.54	37.7	49.82
r9	50.37	45.86	30.25	17.15	16.3	15.87	6.531	6.58	7.579	0.79	0.544	0.897	13.7	11.45	13.22	32.07	39.8	52.74
Avg.	**51.29**	**46.51**	**33.35**	**18.36**	**17.9**	**17.53**	**5.503**	**6.1**	**5.682**	**0.7**	**0.518**	**0.542**	**12.1**	**11.99**	**11.81**	**32.44**	**37.3**	**51.46**
Std.	*20.4*	*19.41*	*18.12*	*4.576*	*4.53*	*4.619*	*5.81*	*6.32*	*5.896*	*2.41*	*1.99*	*2.17*	*9.76*	*9.323*	*10.1*	*20.05*	*20.5*	*20.7*
P_{Base}		8E-07	5E-09		0.45	0.041		0.22	0.514		0.268	0.303		0.835	0.214		0	1E-08
P_{FpP8}			2E-07			0.13			0.375			0.786			0.681			2E-07

1-item Huynh Model Noise

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5
r0	58.44	48.89	62.67	30.68	0.64	34.54	3.444	0.55	1.127	5.11	1.994	1.473	2.65	0.914	0.674	20.84	68.2	20.68
r1	66.46	63.28	45.49	35.84	33.7	4.272	0.662	2.31	5.934	1.78	2.822	8.913	0.92	1.772	4.478	15.62	17.4	52.2
r2	65.12	66.05	59.64	34.89	34.8	32.25	1.213	1.01	2.602	2.13	1.727	3.054	0.8	1.234	1.651	15.17	14.5	20.13
r3	66.84	61.75	60.25	35.46	33.2	33.58	1.281	1.37	1.405	2.05	3.326	2.605	0.86	1.584	0.952	13.78	19	21.46
r4	66.1	61.97	55.61	35.14	32.6	29.92	1.255	2.07	3.911	0.67	3.57	5.241	0.88	1.768	1.586	16.26	18.4	24.04
r5	65.62	67.33	62.5	35.16	35.3	34.14	0.891	1.16	2.236	2.42	1.712	1.314	0.68	0.747	1.025	15.54	14	19.09
r6	66.7	52.39	55.55	35.71	26.6	30.59	0.878	3.47	2.411	1.15	9.212	4.013	0.47	3.534	1.648	15.29	25	25.99
r7	65.48	63.67	61.87	34.82	34.1	33.81	1.342	1.81	1.281	2.18	2.756	2.7	1.14	1.228	0.72	15.57	17	20.15
r8	59.91	42.89	54.3	31.8	21.6	0.869	2.361	7.27	1.977	5.23	10.75	3.079	2.31	5.91	1.011	18.19	31.4	58.56
r9	64.63	57.56	49.48	34.59	29.6	0.674	1.152	4.27	1.144	2.31	6.33	2.615	1.33	2.818	0.772	16.55	20	65.88
Avg.	**64.53**	**58.58**	**56.74**	**34.41**	**28.2**	**23.46**	**1.448**	**2.53**	**2.403**	**2.5**	**4.42**	**3.501**	**1.2**	**2.151**	**1.452**	**16.28**	**24.5**	**32.82**
Std.	*13.5*	*19.98*	*22.56*	*5.241*	*6.17*	*4.669*	*3.25*	*4.15*	*4.545*	*5.47*	*6.97*	*6.37*	*2.66*	*4.236*	*2.493*	*13.03*	*20.4*	*18.3*
P_{Base}		0.014	0.007		0.06	0.045		0.14	0.172		0.097	0.346		0.08	0.617		0.11	0.018
P_{NsP2}			0.549			0.439			0.88			0.47			0.292			0.323

1-item Huynh Model FPR

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5
r0	58.44	63.95	29.75	30.68	35	0.526	3.444	1.02	0.946	5.11	1.784	1.448	2.65	0.617	0.837	20.84	18.8	87.66
r1	66.46	63.18	43.56	35.84	34.8	27.01	0.662	0.95	3.766	1.78	1.616	4.333	0.92	0.634	2.506	15.62	20.1	40.1
r2	65.12	56.36	25.11	34.89	30.9	1.849	1.213	3.06	2.418	2.13	3.976	4.385	0.8	1.748	3.264	15.17	23.3	82.3
r3	66.84	47.75	47.87	35.46	26.6	30.77	1.281	4.68	1.616	2.05	6.967	1.928	0.86	2.959	0.837	13.78	31.3	37.24
r4	66.1	62.72	27.94	35.14	35	0.591	1.255	0.93	0.78	0.67	0.789	1.863	0.88	0.746	0.846	16.26	20.1	88.29
r5	65.62	50.96	51.12	35.16	27.1	31.52	0.891	3.53	0.876	2.42	6.794	1.626	0.68	3.351	1.241	15.54	28.5	33.92
r6	66.7	52.79	27.06	35.71	27.9	0.347	0.878	4.16	1.255	1.15	6.911	1.422	0.47	3.586	0.592	15.29	24.9	89.52
r7	65.48	49.12	22.65	34.82	25.8	2.768	1.342	5.64	2.406	2.18	7.292	5.634	1.14	3.554	2.803	15.57	29.2	84.27
r8	59.91	51.91	27.36	31.8	27.8	1.224	2.361	4.08	1.54	5.23	6.983	2.472	2.31	3.166	0.813	18.19	25.8	86.4
r9	64.63	40.55	27.6	34.59	1.76	0.745	1.152	2.48	0.939	2.31	4.093	1.084	1.33	2.404	0.424	16.55	69.3	89.77
Avg.	**64.53**	**53.93**	**33**	**34.41**	**27.3**	**9.736**	**1.448**	**3.05**	**1.654**	**2.5**	**4.721**	**2.619**	**1.2**	**2.277**	**1.416**	**16.28**	**29.1**	**71.95**
Std.	*13.5*	*19.83*	*43.38*	*5.241*	*6.28*	*3.044*	*3.25*	*4.77*	*3.627*	*5.47*	*7.42*	*5.44*	*2.66*	*3.815*	*2.928*	*13.03*	*15.6*	*40.2*
P_{Base}		0.004	3E-06		0.05	2E-04		0.03	0.666		0.037	0.877		0.061	0.64		0.02	4E-05
P_{FpP8}			6E-04			0.007			0.046			0.052			0.147			6E-04

1-item Adaptive Trust Model Noise

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5
r0	72.44	71.26	72.45	25.83	24.7	19.9	6.56	6.38	6.742	1.65	2.106	2.413	13.6	15.06	18.21	1.06	1.65	1.451
r1	70.99	72.64	74.34	23.43	26.3	20.28	8.375	6.16	6.062	1.75	1.874	2.193	15.6	13.78	17.96	1.102	0.57	0.457
r2	69.73	70.88	73.48	23.98	24.2	22.28	7.45	7.02	5.861	2.57	2.732	2.463	14.5	13.94	14.86	1.088	0.55	0.38
r3	71.34	71.31	74.96	24.5	24.9	23.03	7.289	5.43	5.326	1.95	1.435	1.426	14.5	15.58	14.7	0.72	1.56	0.817
r4	71.97	72.1	73.07	25.15	24.5	20.45	6.18	6.95	5.113	2.65	1.352	1.842	13.5	14.49	17.14	0.821	0.95	2.688
r5	72.46	72.35	73.41	25.31	23.1	20.49	5.27	7.46	8.865	1.91	1.729	1.723	14.7	14.93	14.94	0.676	0.7	0.883
r6	71.89	70.14	72.57	24.74	23.9	21.17	6.516	8.01	5.049	1.92	1.811	2.425	14.2	15.47	16.17	0.895	0.88	2.818
r7	71.84	71.71	73.41	26.74	24	21.73	4.771	6.7	6.663	1.8	2.288	1.526	13.7	14.85	16.27	1.653	0.98	0.919
r8	72.27	71.89	72.91	25.35	25.5	20.13	6.413	5.19	6.756	1.69	1.76	1.979	13.2	14.82	16.63	0.854	0.68	1.397
r9	73.46	71.36	72.96	25.44	23.5	21.03	5.293	7.82	5.549	1.5	1.866	2.114	14.1	14.76	17.67	0.776	1.23	1.234
Avg.	**71.84**	**71.56**	**73.35**	**25.05**	**24.5**	**21.05**	**6.412**	**6.71**	**6.2**	**1.94**	**1.895**	**2.011**	**14.2**	**14.77**	**16.45**	**0.964**	**0.98**	**1.304**
Std.	*11.7*	*12.59*	*11.43*	*4.527*	*4.76*	*4.939*	*6.48*	*6.43*	*5.997*	*4.1*	*4.1*	*4.25*	*11.3*	*11.64*	*10.17*	*3.065*	*3.24*	*3.5*
P_{Base}		0.476	0.012		0.28	1E-05		0.6	0.729		0.803	0.677		0.111	0.001		0.95	0.289
P_{NsP2}			1E-04			5E-05			0.313			0.387			0.008			0.265

1-item Adaptive Trust Model FPR

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5
r0	72.44	72.12	74.9	25.83	25.7	33.86	6.56	6.23	1.91	1.65	2.407	2.129	13.6	13.63	5.087	1.06	1.05	3.287
r1	70.99	72.23	73.51	23.43	25.5	29.9	8.375	4.85	2.916	1.75	2.412	1.924	15.6	14.31	10.39	1.102	1.97	2.646
r2	69.73	71.4	75.2	23.98	24.6	31.99	7.45	6.78	2.839	2.57	2.545	1.613	14.5	12.89	6.918	1.088	1.06	0.758
r3	71.34	73.22	73.97	24.5	27.2	31.62	7.289	3.9	6.431	1.95	1.482	1.385	14.5	13.64	5.928	0.72	0.84	0.924
r4	71.97	72.83	75.21	25.15	25.5	31.8	6.18	4.85	1.929	2.65	2.224	1.576	13.5	14.03	8.59	0.821	0.84	1.215
r5	72.46	72.02	73.69	25.31	26	31.99	5.27	4.62	5.396	1.91	2.262	2.293	14.7	14.71	6.151	0.676	0.7	0.783
r6	71.89	72.6	73.12	24.74	26	29.43	6.516	4.73	6.59	1.92	1.85	1.791	14.2	13.83	8.123	0.895	1.15	1.149
r7	71.84	71.94	73.7	26.74	24.5	29.47	4.771	6.27	4.745	1.8	2.051	1.16	13.7	14.52	10.62	1.653	1.3	0.845
r8	72.27	71.19	74.64	25.35	24.7	33.22	6.413	6.48	3.121	1.69	1.723	2.01	13.2	14.47	5.686	0.854	1.22	1.131
r9	73.46	71.27	73.77	25.44	26	32.06	5.293	5.88	3.609	1.5	2.756	1.66	14.1	13.53	7.924	0.776	1.16	1.532
Avg.	**71.84**	**72.08**	**74.17**	**25.05**	**25.6**	**31.53**	**6.412**	**5.46**	**3.948**	**1.94**	**2.171**	**1.754**	**14.2**	**13.96**	**7.542**	**0.964**	**1.13**	**1.427**
Std.	*11.7*	*11.97*	*9.479*	*4.527*	*4.45*	*4.274*	*6.48*	*5.88*	*5.016*	*4.1*	*4.54*	*3.9*	*11.3*	*10.84*	*7.738*	*3.065*	*3.49*	*3.72*
P_{Base}		0.565	5E-04		0.26	6E-07		0.09	0.007		0.208	0.336		0.472	1E-06		0.14	0.129
P_{FpP8}			2E-04			1E-06			0.081			0.02			2E-06			0.245

2-item traditonal Model Noise

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5	tBase	tNsP2	tNsP5
r0	74.01	74.29	73.41	26.41	27.8	20.69	7.832	7.64	8.156	1.43	0.473	0.893	17.2	17.53	19.09	44.9	44.1	49.32
r1	66.93	72.11	77.72	22.57	26.5	21.99	11.93	7.33	4.95	4.19	0.939	0.559	17.5	16.73	17.54	47.29	47.9	48.71
r2	74.15	72.18	73.56	27.49	26.6	21.79	6.33	6.93	5.061	1.14	0.437	0.309	16.3	17.71	17.94	45.86	47.2	52.77
r3	73.45	74.43	73.72	27.22	27.4	20.93	6.992	7.28	7.203	0.07	0.238	2.438	17.2	17.2	16.35	47.82	46.3	52.06
r4	73.51	74.58	73.93	25.94	26.6	23.32	8.364	7.54	6.149	0.34	1.023	0.397	17.1	17.14	19.16	45.91	44.3	48.37
r5	73.15	74	74.09	25.69	27.8	21.39	8.136	6.87	4.798	0.79	0.642	0.409	16.9	16.84	19.64	45.83	44.7	50.67
r6	73.56	72.96	74.42	27.04	27.6	21.64	7.471	8	6.596	0.54	0.65	0.979	16.5	17.59	17.66	45.61	43.8	49.22
r7	72.12	72.26	74.4	25.87	25.9	22.21	8.271	8.45	6.517	1.61	0.849	1.089	17.2	17.5	16.42	46.01	46.2	50.65
r8	73.91	73.22	73.63	27.08	27.4	22.66	7.675	7.12	6.968	0.5	0.532	0.72	16.1	17.14	17.47	44.64	44.9	48.83
r9	73.71	72.63	72.77	27.34	25.5	21.24	6.747	9.22	5.958	0.91	0.815	1.216	15.8	17.13	17.55	46.56	45.3	52.34
Avg.	**72.85**	**73.26**	**74.16**	**26.26**	**26.9**	**21.78**	**7.975**	**7.64**	**6.236**	**1.15**	**0.66**	**0.901**	**16.8**	**17.25**	**17.88**	**46.04**	**45.5**	**50.29**
Std.	*29.3*	*27.42*	*31.2*	*7.213*	*7.08*	*6.882*	*7.73*	*7.4*	*6.734*	*3.06*	*2.57*	*3.09*	*14.3*	*13.79*	*11.87*	*28.25*	*27.3*	*32.6*
P_{Base}		0.517	0.261		0.23	3E-05		0.57	0.03		0.187	0.606		0.072	0.02		0.13	1E-05
P_{NsP2}			0.177			5E-07			0.004			0.351			0.135			8E-06

2-item traditional Model FPR

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5	tBase	tFpP8	tFpP5
r0	74.01	66.48	45.87	26.41	27.9	25.07	7.832	7.64	8.477	1.43	0.617	0.25	17.2	16.13	17.53	44.9	52.7	74.38
r1	66.93	63.62	43.69	22.57	28.1	25.44	11.93	7.17	8.652	4.19	0.515	0.536	17.5	16.62	14.69	47.29	55.2	78.16
r2	74.15	61.74	51.46	27.49	23.6	27.19	6.33	9.96	6.262	1.14	1.722	0.611	16.3	17.08	14.97	45.86	56.7	70.65
r3	73.45	67.63	52.53	27.22	25.9	27.12	6.992	7.28	7.202	0.07	0.959	0.418	17.2	19	16.78	47.82	52.1	68.72
r4	73.51	66.89	45.13	25.94	26.3	22.13	8.364	6.14	10.75	0.34	0.564	3.589	17.1	17	17.04	45.91	54.5	72.12
r5	73.15	63.62	46.92	25.69	22	24.17	8.136	9.64	9.789	0.79	4.274	0.904	16.9	18.37	15.08	45.83	52.4	73.14
r6	73.56	66.08	48.42	27.04	27.6	25.19	7.471	7.5	6.275	0.54	0.761	0.553	16.5	15.55	15.67	45.61	53.3	74.69
r7	72.12	65.36	50.73	25.87	27.4	26.44	8.271	7.71	6.003	1.61	0.648	0.347	17.2	16.68	17.33	46.01	53.3	70.64
r8	73.91	64.38	46.87	27.08	25	22.59	7.675	8.9	9.86	0.5	0.858	2.921	16.1	17.22	16.5	44.64	53.4	71.32
r9	73.71	64.62	45.78	27.34	25.5	25.86	6.747	6.6	8.38	0.91	1.007	0.857	15.8	19.75	15.25	46.56	53.4	74.88
Avg.	**72.85**	**65.04**	**47.74**	**26.26**	**25.9**	**25.12**	**7.975**	**7.85**	**8.165**	**1.15**	**1.193**	**1.099**	**16.8**	**17.34**	**16.08**	**46.04**	**53.7**	**72.87**
Std.	*29.3*	*28.8*	*25.29*	*7.213*	*7.1*	*6.802*	*7.73*	*7.44*	*7.936*	*3.06*	*3.45*	*3.21*	*14.3*	*13.38*	*12.33*	*28.25*	*28.9*	*28.5*
P_{Base}		4E-06	5E-10		0.71	0.12		0.87	0.762		0.945	0.931		0.291	0.061		0	3E-10
P_{FpP8}			6E-08			0.344			0.672			0.867			0.062			6E-09

2-item Huynh Model Noise

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5	hBase	hNsP2	hNsP5
r0	92.13	93.28	86.94	49.7	50.6	47.77	1.861	1.5	1.987	2.2	1.394	4.12	1.06	0.796	1.823	44.9	24.6	29.54
r1	89.92	75.88	66.55	48.78	42.2	4.201	1.999	4.83	6.728	3.19	7.555	10.14	1.22	3.378	4.125	47.29	37.8	79.89
r2	91.12	79.09	71.42	50.18	41.2	0.773	1.741	5.45	0.688	1.69	7.104	3.145	1.24	4.933	0.573	45.86	33.8	95.02
r3	92.83	92.73	72.8	50.18	50.4	2.744	1.117	1.31	3.209	2.27	2.468	5.227	1.54	1.219	2.801	47.82	25.2	86.52
r4	92.09	83.73	86.11	49.89	43.9	48.11	1.179	5.29	1.113	2.91	5.892	2.732	0.88	3.794	1.287	45.91	29.1	32.34
r5	89.32	84.09	82.4	48.17	44.4	45.32	2.622	3.83	3.112	2.41	5.064	4.101	2.03	3.148	1.535	45.83	30.6	34.72
r6	89.72	89.89	72.28	48.32	48.3	1.146	1.783	2	1.416	3.89	2.86	3.263	1.42	0.988	0.988	45.61	27.1	92.04
r7	91.45	86.42	72.47	49.98	46.6	0.689	2.069	3.26	1.478	2.16	5.55	3.19	1.04	2.389	1.614	46.01	27.6	92.31
r8	84.8	90.51	82.52	45.77	49.1	46.63	3.17	1.38	2.594	5.63	2.376	2.895	2.3	1.106	0.936	44.64	26.1	35.01
r9	92.93	89.19	71	49.96	48.9	3.698	1.193	1.83	2.556	1.37	2.069	3.897	1.43	1.256	1.879	46.56	28.2	88.35
Avg.	**90.63**	**86.48**	**76.45**	**49.09**	**46.6**	**20.11**	**1.873**	**3.07**	**2.488**	**2.77**	**4.233**	**4.271**	**1.41**	**2.301**	**1.756**	**46.04**	**29**	**66.57**
Std.	*18.6*	*22.51*	*46.11*	*7.088*	*9.61*	*4.907*	*4.2*	*5.83*	*4.793*	*6.24*	*8.22*	*8.56*	*3.36*	*4.663*	*3.332*	*28.25*	*22.8*	*45.8*
P_{Base}		0.062	4E-04		0.07	0.004		0.07	0.291		0.125	0.096		0.119	0.39		0	0.05
P_{NsP2}			0.002			0.005			0.458			0.963			0.371			0.002

2-item Huynh Model FPR

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5	hBase	hFpP8	hFpP5
r0	92.13	84.89	50.96	49.7	47.5	39.08	1.861	2.06	2.239	2.2	2.683	2.13	1.06	1.957	2.133	44.9	33.1	75.65
r1	89.92	79.1	57.88	48.78	43.8	38.52	1.999	4.57	3.39	3.19	6.071	4.957	1.22	2.489	2.849	47.29	35.6	64.04
r2	91.12	81.86	59.06	50.18	46.2	40.47	1.741	2.42	2.543	1.69	3.111	4.787	1.24	1.655	1.248	45.86	36.3	63.51
r3	92.83	83.14	61.04	50.18	47.9	42.33	1.117	1.8	1.533	2.27	2.287	2.397	1.54	0.991	1.334	47.82	37.2	64.67
r4	92.09	57.41	59.07	49.89	0.96	42.07	1.179	1.4	1.074	2.91	2.015	2.256	0.88	0.971	0.67	45.91	109	66.56
r5	89.32	79.3	30.1	48.17	46.7	0.795	2.622	0.92	1.19	2.41	2.84	1.57	2.03	1.077	0.72	45.83	40.3	136.8
r6	89.72	72.03	59.99	48.32	39	42.11	1.783	5.2	1.013	3.89	10.64	2.293	1.42	4.444	0.743	45.61	39.8	64.99
r7	91.45	83.21	56.61	49.98	48.2	39.49	2.069	1.58	2.557	2.16	1.3	4.226	1.04	0.95	1.827	46.01	36.5	67.04
r8	84.8	79.78	18.89	45.77	41.9	9.67	3.17	3.95	15.27	5.63	7.095	18.13	2.3	3.912	12.1	44.64	34	96.54
r9	92.93	72.5	30.81	49.96	40.9	0.807	1.193	4.95	0.817	1.37	6.502	2.132	1.43	3.626	0.628	46.56	42.9	136.2
Avg.	**90.63**	**77.32**	**48.44**	**49.09**	**40.3**	**29.53**	**1.873**	**2.89**	**3.163**	**2.77**	**4.455**	**4.488**	**1.41**	**2.207**	**2.425**	**46.04**	**44.5**	**83.6**
Std.	*18.6*	*28.84*	*36.69*	*7.088*	*8.45*	*6.483*	*4.2*	*5.06*	*4.874*	*6.24*	*8.42*	*7.2*	*3.36*	*4.239*	*4.024*	*28.25*	*31.1*	*35.6*
P_{Base}		0.001	7E-06		0.09	0.006		0.1	0.321		0.066	0.214		0.076	0.347		0.83	0.003
P_{FpP8}			7E-04			0.202			0.842			0.984			0.833			0.012

2-item Adaptive TrustModel Noise

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5	aBase	aNsP2	aNsP5
r0	102.3	103.4	104.5	35.89	36.1	32.04	9.816	8.54	9.994	2.79	1.86	3.373	19.7	20.62	20.68	1.695	1.68	1.559
r1	102.1	102	103.2	35.7	34.9	30.96	10.49	9.68	10.51	3.48	2.052	3.286	19	21.62	21.82	0.887	1.38	1.827
r2	101	102	105.7	35.62	35.6	30.66	12.67	8.83	9.562	2.81	1.967	0.627	17.8	21.83	24.36	1.637	1.34	0.745
r3	103.1	103.8	106.2	36.39	35.9	31.26	9.151	9.84	8.026	2.37	1.226	2.831	20.6	20.77	23.6	1.775	1.71	1.419
r4	102.2	102.5	107	36.65	35.5	31.65	9.756	10.5	7.023	3.49	2.536	1.323	18.7	19.64	21.86	0.889	1	2.872
r5	101.6	103.2	105.6	33.71	37.6	29.66	11.1	8.03	10.41	3.17	2.894	1.877	20.6	17.94	22.41	1.03	1.59	1.201
r6	103.8	100.6	103.3	36.11	35.9	30.86	9.216	9.85	7.774	1.69	2.662	3.85	19.1	20.38	23.85	1.217	1.73	1.518
r7	102.1	102.6	106.5	36.01	35.7	31.96	10.61	10.2	8.665	2.06	2.404	1.668	19.8	20.07	21.07	1.084	0.7	1.914
r8	101.7	90.51	103.6	34.96	49.1	28.96	9.187	1.38	9.155	3.02	2.376	2.254	20.1	1.106	23.83	1.653	26.1	2.825
r9	102.3	102.6	103.3	36.97	36.9	29.61	9.047	8.66	10.91	3.16	2.164	4.049	19.1	19.39	21.77	0.787	1.64	1.737
Avg.	**102.2**	**101.3**	**104.9**	**35.8**	**37.3**	**30.76**	**10.1**	**8.56**	**9.202**	**2.8**	**2.214**	**2.514**	**19.5**	**18.34**	**22.52**	**1.265**	**3.89**	**1.762**
Std.	*16.9*	*17.61*	*15.34*	*7.028*	*7.2*	*7.229*	*8.7*	*8.32*	*8.685*	*5.54*	*5.01*	*5.3*	*15.8*	*14.54*	*12.75*	*4.334*	*6.34*	*5.06*
P_{Base}		0.488	0.001		0.33	1E-07		0.1	0.089		0.032	0.524		0.598	3E-04		0.31	0.095
P_{NsP2}			0.012			0.002			0.54			0.486			0.078			0.392

2-item Adaptive Trust Model FPR

	BuyerTkGn			1GSellerTkGn			0.8GSellerTkGn			0.5GSellerTkGn			S1SellerTkGn			S2SellerTkGn		
Round	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5	aBase	aFpP8	aFpP5
r0	102.3	104.7	105.7	35.89	36.5	39.51	9.816	10.9	4.378	2.79	2.201	1.874	19.7	16.91	19.29	1.695	1.01	1.432
r1	102.1	100.6	106.1	35.7	35.2	44.72	10.49	8.72	4.584	3.48	3.216	2.003	19	22.24	10.51	0.887	1.69	3.712
r2	101	101.4	102.9	35.62	34.2	38.53	12.67	9.54	3.238	2.81	2.953	2.416	17.8	20.99	21.21	1.637	2.56	3.311
r3	103.1	104.2	108.1	36.39	37.4	40.64	9.151	8.95	6.359	2.37	2.171	1.845	20.6	19.07	14.67	1.775	1.58	1.708
r4	102.2	103.6	104.5	36.65	35.8	39.01	9.756	10.4	5.365	3.49	2.289	2.853	18.7	18.59	19.02	0.889	0.97	0.991
r5	101.6	102.2	103	33.71	36.9	37.93	11.1	7.86	7.325	3.17	2.44	2.621	20.6	20.58	18.47	1.03	1.19	1.806
r6	103.8	101.8	102.9	36.11	36.5	40.54	9.216	8.45	5.905	1.69	3.739	1.531	19.1	18.75	16.1	1.217	1.93	4.196
r7	102.1	104	101.6	36.01	36.7	42.15	10.61	8.34	4.01	2.06	3.068	1.756	19.8	18.75	18.78	1.084	0.84	3.466
r8	101.7	102	104.9	34.96	36	38.45	9.187	9.22	5.243	3.02	1.963	2.488	20.1	19.82	18.84	1.653	1.57	0.632
r9	102.3	100.4	103.1	36.97	35.4	39.71	9.047	11.5	6.987	3.16	2.736	1.614	19.1	19.6	17.9	0.787	1.68	2.024
Avg.	**102.2**	**102.5**	**104.3**	**35.8**	**36.1**	**40.12**	**10.1**	**9.39**	**5.34**	**2.8**	**2.678**	**2.1**	**19.5**	**19.53**	**17.48**	**1.265**	**1.5**	**2.328**
Std.	*16.9*	*17.64*	*17.17*	*7.028*	*7.19*	*7.083*	*8.7*	*8.81*	*6.385*	*5.54*	*5.46*	*4.91*	*15.8*	*16.14*	*15.6*	*4.334*	*4.88*	*5.8*
P_{Base}		0.601	0.008		0.58	7E-05		0.26	7E-05		0.698	0.001		0.909	0.089		0.21	0.038
P_{FpP8}			0.027			3E-04			6E-05			0.07			0.13			0.046

APPENDIX D

VALUES OF PARAMETERS USED IN THE SIMULATION

Notation	Description	Value
η_D	The learning rate for the weight of Estimated Direct Reputation	0.1
η_W	The learning rate for the weight of Estimated Witness Reputation	0.1
β_p	The weight for positive ratings	0.6
β_n	The weight for negative ratings	0.9
c_{tm}	The ad hoc constant for computing $w_{tm}(t)$	ln(0.5)/30
c_{cn}	The ad hoc constant for computing $\rho_{D_{cn}}(t)$	0.005
c_{pv}	The ad hoc constant for computing $w_{pv}(t)$.	- ln(0.9992)
c_{tc}	The ad hoc constant for computing $\rho_{W_{tc}}(t)$.	0.005
c_{wc}	The ad hoc constant for computing $\rho_{W_{wc}}(t)$.	0.1
thresholdRepu	Threshold for S1Sellers and S2Sellers to start abusing reputation	0.5
cpLSV	LSV for inexpensive items	2
exLSV	LSV for expensive items	8
m	Profit margin	0.3
g	Positive real number which is smaller than m. It determines the mean actual service values of the sellers.	0.2
T	The temperature value for Bolzmann Distribution	0.2

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