Determinants of escrow service adoption in consumer-to-consumer online auction market: An experimental study

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Abstract

Risk relief services (RRSs), as complementary to online trust promoting services, are becoming versatile options for risk reduction in online consumer-to-consumer auctions. In this paper, we identify factors that affect the behavior of buyers in an online auction market who had to either adopt or not adopt online escrow services (OES). An experimental C2C auction system with embedded decision support features was used to collect data. Results show that market factors, such as fraud rate, product price, and seller’s reputation are important in determining buyers’ OES adoption. This study also finds that sellers’ reputation has a significant effect on buyer’s risk perception, which influences his OES adoption decision. Furthermore, the buyers’ OES adoption decisions were found to be congruent with the implied recommendations that were based on expected utility calculations.

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1. Introduction

The consumer-to-consumer (C2C) online auction market has undergone rapid growth in the last few years. However, increasing online fraud has been haunting tens millions of traders in the market [2]. It was reported that among the 35.6 million Americans who participated in online auction, more than 40% have encountered Internet fraud problems [16]. In 2003, among the 37,183 complaints reported to Internet Fraud Watch, 89% were related to online auctions [17]. According to Internet Fraud statistics, online auctions continue to be the most fraud prone Internet service [18]. Traders in C2C online auction markets have limited information to estimate the risk in transacting with others. The high risk of online trading fraud coupled with low trust in potential trading partners significantly affects traders’ willingness to trade [2]. Although governments are refining the legal system to protect online businesses, the legislation process is falling behind the growth of electronic commerce [19,28].

The impersonal nature of online transactions and information asymmetry remains the main obstacle to building trust between seller and buyer. For an opportunistic trader, the information asymmetry provides an opportunity to benefit by defrauding the trading partners [25]. For an honest trader, the disadvantages arise from the spatial and temporal separation caused by the communication media [9].

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To promote willingness-to-buy, trust-building is crucial in risky situations [27]. Trusting means to take risks and leave oneself vulnerable to the actions of others [23]. The level of trust strongly influences the trader’s behavior [41]. For promoting online trust, the services by trusted third parties (TTPs) can be effective by generating trustworthy trade procedures [14], such as the trust seal services [24]. In addition, the online reputation system plays an important role in providing the needed information in the adoption of TTPs’ services [5,11,34,44]. However, typical TTP services, such as the online trust sign, are merely aimed at promoting the seller’s trustworthiness in the online market [24]. For buyers, TTP services can only reduce the risk but not eliminate it. Emerging risk relief services (RRSs), on the other hand, can eliminate risk.

The business models used by RRSs vary. There are online debit accounts (e.g. www.PayPal.com), and online escrow services (OES) (e.g., Payflow Pro™ by VeriSign, eMoneyMail™ by Bank One, QuickCash™ by AOL). Among these services, OES not only passively compensate the losses, but also eliminate C2C fraud if every online C2C transaction adopts it [25,53]. Thus OES is effective both in trust-building and in risk-elimination [37,53]. However, “only 6% of those who have bought items have paid through an online escrow service” [16]. It is important to study the reason behind non-adoption of OES by online auction users, so that proper remedial procedures can be implemented. From an academic perspective, it is important to understand the factors that influence the decision-making behavior of online auction users so that theoretical models can be developed for further investigation.

In this paper, we study the behavior of buyers in a simulated C2C market place and analyze the factors that affect their perceptions of risk and their subsequent decisions to adopt OES. In particular, we are interested in exploring the effects of perceived risk, sellers’ reputation, and price of product on OES adoptions. We developed an experimental system with decision support capabilities to study the OES adoption behavior. Using the system, we collected transaction level data to investigate the factors that would help in describing risk perception and decision-making behavior of buyers.

The rest of the paper is organized as follows: Section 2 covers the theoretical background for this research; Section 3 presents the factors that might influence the decision-making and the hypotheses that will be tested; Section 4 describes the experiment; and Section 5 provides the results of the experiment. We discuss the findings and provide implications for practitioners and academics in the last section.

2. The rationale for the research

Risks in online transactions critically affect online traders’ adoption of trusted third parties’ services [25]. The risk a buyer perceives is a subjective estimate of the objective risk and is defined as “a decision-maker’s assessment of the risk inherent in a situation” [40]. It is a proxy for the objective risk in a real-world situation, and becomes the basis for people’s decisions and choices [51]. In online markets, perceived risk is the buyer’s perception of the uncertainty and the possible adverse consequences of buying from a seller [12]. Perceived risk has been found to influence the purchase intention [47].

Since the adoption of OES can effectively eliminate the online transaction risk, rational buyers would weigh the decision of OES adoption using the cost for OES fee and the risk of suffering some loss. They would make the decision according to the expected utility. Expected utility theory [3,13,49] can be used to explain people’s decisions under uncertainty. People choose the alternatives with the highest expected utility if they are consistent with the basic behavioral axioms [49]. We find that expected utility theory is applicable to the study of OES adoption.

In the C2C online auction market, it is hard to find the identity of a trader. The intangible risk of trading with him can only be perceived and estimated using observable indicators, namely his online reputation rating [32]. Reputation is a general term in common business research and practice. In the context of business practices, reputation indicates the standing of a firm in its relationship with its competitors, suppliers, buyers, and other types of partners [15]. A firm’s reputation is a critical factor in various managerial decision-making processes [8,15]. It has been found that online reputation has an impact on buyers’ trust in a seller in the same way it does in a physical market [4,5]. It affects the buyer’s perceived risk because reputable vendors are more likely to commit to good behavior in accordance with the contract or agreement for fear of damaging their reputation, while less reputable vendors may indulge in unfavorable behavior [11,44,53]. Therefore, online reputation plays an important role in OES adoption decision-making.

From the above discussion, we can identify a causal relationship chain starting from online reputation, then perceived risk, and ending at OES adoption. In addition, there are a number of other factors that affect the buyer behavior in general. However, the effects of online reputation on decision-making with regards to perceived risk are not well investigated, and there has been no empirical study in OES adoption so far.
3. Factors that affect the adoption decision

The decision of whether or not to purchase OES protection is the primary focus of this study. There are a number of possible determinants for OES adoption decision. They are (a) seller’s reputation, (b) buyer’s perceived risk, (c) fraud rate, (d) price of product, (e) buyer’s defraud experience, (f) buyer’s risk attitude, and (g) buyer’s expected utility. All are important factors to study. Among these factors, fraud rate, reputation, risk attitude and defraud experience are unique to individual traders and we name this group the Market level factors. Perceived risk, risk attitude and defraud experience are unique to individual traders and we name this group Personal level factors.

3.1. The OES adoption decision

Purchasing OES would cost the buyer a nominal amount; not purchasing OES can potentially save some money. However, if the buyer is defrauded in a transaction, and he did not purchase OES, he stands to lose the amount he paid to purchase the product. On the other hand, if he had bought OES, he would be protected against such fraud.

3.2. Perceived risk

It has been shown that perceived risk (PR) is a significant factor in the context of online transactions [31] and that it is an important variable that affects perceived customer value and ultimately the decision to purchase a product [43,45]. In online trades, financial risk is considered a key risk [42] which can be lowered by warranties and money back guarantees. However, purchase of OES for specific trade will eliminate the financial risk altogether. In the case of OES adoption, the user’s perception on whether he is likely to be cheated will ultimately determine his decision to purchase OES protection. Hence, our first hypothesis is

**H1. OES adoption is positively associated with perceived risk.**

3.3. Risk attitude

Risk attitude is the tendency of a decision maker to take risky actions, and it contributes significantly to decision-making [29]. Risk behavior is categorized into three types: risk-seeking, risk-neutral, and risk-averse. Within a given context, people exhibit relatively stable risk behavior depending on their risk attitude [22].

It has been established that an individual’s risk attitude is a personality trait and that it is invariant across task situations [51]. Hence, we can expect that risk attitude is invariant during OES adoption decisions. In online trading, the trader may either choose to use OES or not. Transacting without OES is a risk-seeking behavior because it has an uncertain outcome, which may result in financial loss due to being defrauded. Adoption of OES eliminates the probability of financial loss since it guarantees the trader will not lose money due to cheating, so transacting with OES is a risk-averse behavior. The empirical literature also suggests that risk attitude may impact risk perception [7,48].

OES adoption problem involves weighing the risk of being cheated versus the chance of not being cheated. So we can expect that the individual’s risk attitude will be an important factor. The effects of risk attitude on OES adoption will be indirect with the trader’s perceived risk being the intermediate variable. Hence, our next hypothesis is stated as

**H2. Buyer’s perception on risk is influenced by his risk attitude.**

3.4. Reputation

In the absence of first-hand knowledge about the seller, the reputation of the seller becomes an important factor for decision-making [1,35]. Reputation can signal the trustworthiness of sellers and the risk in online transactions with them [39]. Trustworthiness reflects the buyer’s belief about the quality of products and services [10]. Hence, a buyer’s perception of whether he will be cheated or not depends on the reputation of the seller. This leads to our next hypothesis, which is stated as

**H3. Seller’s reputation will negatively affect the buyer’s perception of risk.**

In addition, it can be expected that reputation will be a significant factor for the market in general. Regardless of whether a buyer is risk-seeking or risk-averse or whether the product is expensive or inexpensive, reputation can be expected to affect the buyer’s decision to purchase OES protection. This leads to our next hypothesis, which is stated as

**H4. OES adoption is negatively associated with the seller’s reputation.**
3.5. Product price

Product price plays an important role in purchasing and financial decisions. The risk of an incorrect assessment of a product is proportional to the price of the product [38]. So, the price of the product being traded is an inherent component of perceived risk [21]. In the C2C market, the quality of the specific product being sold cannot be ascertained until the product is received and inspected by the buyer, so buying in a C2C market is a risky proposition. But, for low value transactions, more people would be willing to take this gamble, as compared to high value transactions [20]. This leads to our next hypothesis, which is stated as

H5. Perceived risk will be positively associated with the price of the item being transacted.

It has been shown that people tend to be risk-seeking when the stakes are low, and risk-averse when the stakes are high [20]. Assume that there is a fixed opportunity cost for a dishonest seller to cheat. A fraud involving a high-priced item is attractive to the dishonest seller and will lead to loss for the buyer, if the buyer does not purchase OES. For low-priced items, a potentially dishonest seller may choose not to defraud because the opportunity cost may be higher than the benefit from cheating. Similarly, a buyer may choose not to purchase OES because the cost of OES may be greater than the expected loss from fraud. Hence, the buyer may be less inclined to purchase OES. In OES adoption, we can expect that low-priced items will attract fewer instances of OES adoption than high-priced items. This leads to the next hypothesis, which is stated as

H6. OES adoption is positively associated with the price of the item being traded.

3.6. Fraud rate

Fraud rate is an indicator of fraud in the market and reflects the average risk level caused by fraud. Although it cannot tell exactly how risky a specific transaction is, it does signal the relative level of risk compared with the same figure in different time points. If the market level fraud rates were high, buyers would perceive a higher risk and would subsequently be more willing to purchase OES protection. This leads to the next hypothesis that

H7. Fraud rate will positively affect OES adoption.

3.7. Defraud experience

Past behavior is an important factor that affects online shopping habits [6]. A buyer’s past experience of being cheated would make him more cautious in the future, and he might choose to purchase OES protection more often. Thus, the next hypothesis is

H8. A buyer is more likely to adopt OES after a defraud experience.

The eight hypotheses are presented in the Research Model in Fig. 1. The labels on the arrows represent the hypotheses to be tested by the relationship. OES Adoption is the dependent variable. The boxes representing independent variables are grouped into two sets. The first set, shown within a dotted line boundary, represents the market factors. This set contains Fraud Rate, seller Reputation, and Product Price, and they are used to determine the OES adoption behavior of the buyer (H4,
H6 and H7). The second set, shown within the dashed line, includes factors that affect the risk perception of the buyer. *Perceived Risk* is central to this set, and it is hypothesized to be dependent upon the buyer’s risk attitude, the reputation of the seller, and *Product Price* (H2, H3 and H5). Subsequently, *Perceived Risk* affects the *OES Adoption* (H1). The first part of the model captures the effects of market factors on the OES decision, whereas the second part of the model attempts to capture the congruence between *Perceived Risk* and *OES Adoption*. The diagram includes a relationship between the *OES Adoption* and *Defraud Experience* of the buyer (H8).

Next, we describe how these constructs are operationalized.

### 4. Research method

To determine the effects of different factors on OES adoption, variables such as reputation and price must be controlled. So, we used the lab experiment research method. The software system provided decision support and information services by which subjects could decide whether or not to adopt OES. Use of an experimental method to study the OES adoption decision is acceptable. According to Ref. [52], everyday simple decisions that involve monetary risks can be validly studied in controlled laboratory settings, provided that the magnitudes of the outcomes are reasonably small and that the decisions are not “high stakes” decisions involving personal injury, or life and death. The experiment we conducted is not a lab experiment in the traditional sense. The subjects could complete the assigned tasks from the comfort of their homes. It can be called an online field experiment (see for example, [4]).

#### 4.1. Operationalization of constructs

Most Internet users are aware of the possibility of being defrauded. Their perception of risk of being defrauded can be the same or different from the market fraud rate. Our formulation of perceived risk (PR) captures any change in the user’s risk perception as compared to the prevailing market fraud rate (FR). To measure the user’s perception, we get two inputs on change in perception using two questions from the buyer. The first question, “In general, what do you think of the risk of being cheated in comparison with market average?”, is used gather what we call “Change in Base Perceived Risk (ABPR). The answer can be one of seven choices, namely (a) the same (0%), (b) Little lower (−15%), (c) Fairly lower (−30%), (d) Much lower (−45%), (e) Little higher (+15%), (f) Fairly higher (+30%), and (g) Much higher (+45%). The second question, “For this trade partner, what do you think of the risk of being cheated?”, was used to gather “Change in Dynamic Adjustment Rate” (ΔDAR). The choices for the second question are (a) the same (0%), (b) Little lower (−20%), (c) Fairly lower (−40%), (d) Much lower (−60%), (e) Little higher (+20%), (f) Fairly higher (+40%), and (g) Much higher (+60%). PR is FR adjusted with these two inputs from the user. The formulation of PR is

\[
FR \times (1 + ABPR) \times (1 + ΔDAR)
\]

So, for each trade, the perceived risk may be higher than or lower than or the same as the market fraud rate.

Risk attitude refers to a person’s inherent attitudes towards risk. Measuring the risk attitudes of individuals has typically been accomplished using lotteries and what-if type questions that compare a person’s preferences between “sure things” and uncertain alternatives [26]. In this study, we used questions similar to the ones reported in [26] to identify subjects’ general risk attitude (see Appendix A).

In C2C online auction marketplaces, reputation becomes the single most important tangible asset for online traders. Presentation of information on reputation is a key characteristic of a trustworthy online system [36]. In most cases, reputation is based on opinions of others. In current C2C online auction markets, reputation is also based on the feedback from customers. Typically, the cumulative number of positive feedbacks and negative feedbacks are reported for each trader. Positive comments are rewarded with a rating of +1, neutral comments with 0, and negative comments with −1. We used net reputation scores as the indicator of online reputation, since it has a significant effect on price decisions and the number of bids [34]. Typically, reputation scores are almost always greater than 0. For a very small number of cases, it can be 0. A low reputation score would indicate that either the seller has not yet established his reputation or he had recently defrauded. In either case, buyers would be cautious about transacting with him. For the experiment, reputation scores were randomly generated from a geometric distribution (see [33] for details).

Price is defined as the winning price at the end of the bidding phase. Most C2C transactions are low priced, and some are high priced. Two levels of price, *High* (mean=$1380) and *Low* (mean=$150), are used in the experiments to test their effects on dependent variables.
The number of low-valued transactions is proportionately more than the high-valued transactions. Fraud rate refers to the overall cheating rate on the online auction market. Two levels of FR (High and Low) are used in the experiment to test its effects on dependent variables. In our simulated C2C market, some transactions resulted in defrauding the buyer. The seller’s reputation data was used in generating such defrauding experience. The system was designed to induce a fraud if \( x < p \), where \( x \) is a random number generated from a uniform distribution \([0,1]\) and \( p \) is computed as

\[
p = (0.45 - \ln(R_t/40 + 0.001)) \times 1.5 \times FR
\]

where \( R_t \) is a positive reputation score. An analysis of the above formulation would reveal that sellers with a very low reputation 1 or 0 are certain to cheat, and sellers with high reputation score of 54 or more are certain not to cheat. The value of \( p \) decreases in a non-linear manner between the extreme reputation scores.

The experimental system computes expected utility figures which can be used for making the decision. ‘Expected net benefit with OES’ is computed as \( \text{Net Benefit} - \text{Price} \times \text{OES Fee Rate} \) and ‘Expected net benefit without OES’ is computed as \( \text{Net Benefit} \times (1 - \text{Perceived Risk}) - (\text{Perceived Risk} \times \text{Price}) \), where \( \text{Net Benefit} \) is defined as the difference between the buyer’s perceived value and the winning price. Perceived Value is randomly generated by the experiment system as a positive value that is proportionate to the Price. Such formulation of perceived value is acceptable, since a rational buyer would agree to make a purchase only if he perceives the value of the product to be higher than the price he is paying for it.

### 4.2. Subjects

Students from a large public university who had enrolled in an Introduction to Data Communications course volunteered to participate in the study. Statistics on subjects’ experience with online buying and OES is shown in Table 1. We tested to see if any of these characteristics would explain the OES adoption behavior by running the ANOVA with individual buyers’ OES adoption rate (number of times OES was adopted/number of completed trades) as the dependent variable and the demographic variables as independent variables. The ANOVA results indicated that none of the four variables was significant (at alpha=0.05 level) in explaining the variance in individual buyers’ OES adoption rate. Hence, any observed effects are attributable only to the experimental conditions.

It is desirable that the subjects behave like real online auction participants. We offered a standard prize of $10 to each participant. In addition, to simulate the economic environment, we offered prize money ranging from $5 to $30 for the more efficient users of the allocated funds. Subjects were told prior to the experiment that only a few of them could get the prize and that there would be only one $30 prize winner, one $20 winner, four $10 winners and twelve $5 winners. We believe that the subjects were well motivated to behave like buyers in an actual trade environment. In all, 97 subjects volunteered for the study. A 20-min lecture on online auction and escrow service was offered to subjects. The lecture covered an introduction to escrow services for online C2C auctions, the experimentation plan, and the benefits of participation. Then the subjects completed a risk attitude questionnaire (see Appendix A). Of the 97 subjects who completed the risk attitude questionnaire, only 95 signed up on the system to complete the trades. Their background information is shown in Table 1.

#### 4.3. Decision support for OES adoption

The experimental system is a web-based simulated C2C auction system. We used JavaScript to provide interactivity at the front-end. The front-end also provides expected benefit estimates, thus facilitating decision support. See Fig. 2 for an annotated screenshot of the interface with decision support and information services.

The server-side application was written using CGI scripts. Three types of functions are implemented in the server-side application They are (1) user interaction functions, such as user authentication, bidding/selling facilities, market status feedback, and reputation report; (2) trade data generation functions, such as merchandise posting, pricing, fraud generation; and (c) database access functions such as dynamic recording of user choices and transactions data. See Appendix B for a list of features of the system.

#### 4.4. Data collection

Each subject logged into the web-based system using a unique user ID and a password. Each subject was
requested to complete 80 trades. (See Table 2 for the distribution of trades). To begin with, each subject was allocated $40,000 as virtual purse money for buying the 80 items. For each trade, the buyer could choose either to purchase the item at the specific final bid or skip purchasing. If he decided to purchase the item, he was required to indicate his perceptions on relative risk, by choosing one of the six options. Then he was required to indicate whether he wished to adopt OES or not. If he chose to adopt OES, the OES service charges were deducted from his purse. If he chose not to adopt, but was cheated by the seller, the system forfeited the amount he paid the seller.

Subjects were allowed to perform the required experiment process either at the University’s computer labs or wherever an Internet connection was available. Most subjects completed all 80 trades in one session. The subjects were requested to use all the information available to them on screen before making the decision. The overall performance of subjects was assessed by the amount of net benefit from trading as a proportion of the total transaction amount. This measure was used only for disbursing the prize money.

5. Results

Ninety-five subjects logged onto the system to complete 80 transactions each. However, subjects were allowed to not commit to a transaction and skip purchasing an item. In addition, the simulation system may have introduced a cheat during those 80 transactions. After such a defrauding experience, the subject might alter his decision-making strategies. We wished to eliminate the effects due to being cheated and consider only those transactions in which subjects actually bought something. After elimination, the number of transactions that were used for testing H1 through H7 was 5708. On average, we have 60 transactions per subject. Of the 5708 transactions, nearly a fourth used OES. Summary statistics of the variables are shown in

<table>
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<th>Product price</th>
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<tbody>
<tr>
<td>Low</td>
<td>30</td>
<td>10</td>
</tr>
<tr>
<td>High</td>
<td>30</td>
<td>10</td>
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</table>
Table 3. Reputation scores had to be scaled down by a factor of 10, since interpretation of its parameter estimate in logistic regression would be more meaningful with increments of 10, rather than increments of one.

To test the Market Factors model, logistic regression with price, fraud rate, and reputation were used as the explanatory variables. SAS’s PROC LOGISTIC routine was used to run the regression. The results are shown in Table 4.

It can be seen that price, fraud rate, and reputation are significant factors in describing the OES adoption behavior. The signs of the estimates are also in the expected directions. These data supports the hypotheses that price positively affects OES adoption (H6), prevailing market fraud rate affects OES adoption (H7), and reputation of the seller affects OES adoption (H4). Analysis of the Perceived Risk Factors Model involves (a) fitting perceived risk as a function of reputation, risk attitude, price, with interaction between risk attitude and price and (b) fitting OES adoption behavior as a function of perceived risk. For (a) we control for defraud experience by using data only up to the first transaction in which the subject was cheated. The results of SAS’s PROC REG routine is shown in Table 5.

From Table 5, it may be noted that only reputation was found to be significant in describing variance in perceived risk, thus supporting H3. The effects of risk attitude on perceived risk (H2) and effects of price on perceived risk (H5) were not found to be significant. The results of logistic regression between OES adoption and perceived risk are shown in Table 6. It may be noted that perceived risk was found to be significant in explaining the OES adoption behavior. Thus, our hypothesis H1 is supported.

When we compare the Goodness of fit for the Logistic regressions in the Market Factors Model and Perceived Risk Factors Model, we find that the Market Factors Model has larger $\chi^2$ value per degree of freedom. Therefore, the Market Factors Model fits the data better than the Perceived Risk Factors Model.

To test the effects of being defrauded on OES adoption behavior, we computed the OES adoption rate before being defrauded and compared that with the adoption rate after being defrauded. OES adoption rate was computed as the proportion of trades that involved the adoption of OES over all the transactions. Using a paired $t$-test, we found that there was no significant difference ($t=1.45$, $p=0.1570$). Thus, H8 was not supported.

5.1. Exploratory analysis

In addition to the pre-specified hypotheses, we sought to find if the decisions suggested by Expected Utility calculated by the experimental system were congruent with the decisions that subjects made. Utility theory [49] rests on two components: probabilities for representing the uncertainty about the consequences, and utilities for representing the preference. The system displayed the expected benefits with OES as well as the expected benefits without using OES. For each transaction, the subjects could have used these figures in making the OES adoption decisions. The frequency counts of transactions could be tested for association between expected utility and the OES decision. The frequency counts for this test are shown in Table 7.
χ² tests on the frequency counts controlled for the risk attitude consistently showed significant associations between the column variable and row variable. The Cochran–Mantel–Haenszel statistics for testing correlation is 1767 (p<0.0001). Thus, we find that there is a high correlation between what was suggested by the Expected Utility figures and the actual behavior of the subjects.

6. Discussions and implications

In this paper, we studied the OES adoption behavior of buyers in a controlled C2C environment. We examined the data using two models, one using only the market factors, and the second using personal factors. Of the eight hypotheses, we found support for six. The interpretations of the results are presented below.

Price of the product, seller’s reputation, and prevailing fraud rate were found to be significant in explaining the OES adoption behavior. Results of the Logistic regression are better understood by running sensitivity analyses. Specifically, we can test how sensitive OES adoption decision is to changes in product price, seller reputation, and fraud rate. LeClere [30] describes a methodology that can be used for this. First, we computed the base probability by using the mean values of independent variables and the coefficients of the logistic regression. To study the sensitivity, we vary the value of one independent variable, fixing the other independent variables at their mean values, and study the effects on the probability. The computed probability is then compared with the base probability. For the fitted model, the base probability is 0.187. Changes to the base probability are determined by manipulating one independent variable value at a time. The results of this analysis are shown in Table 8.

It is apparent that among the three factors, changes in prevailing fraud rate and product price have the strongest effect on the probability of OES adoption. Changing product price from Low to High results in a change of OES adoption probability from 17.2% to 21.1%, and changing fraud rate from Low to High resulted in a change in OES adoption probability from 16.6% to 20.3%. Changing Reputation from mean to mean +10 resulted in a marginal decrease from 18.7% to 17.6%. When the reputation score is changed from mean to 0, (i.e. either seller is a new trader, or he had just defrauded a buyer), the probability of OES adoption increases to 51.7%. Based on the above findings, we recommend that the C2C service providers should provide detailed reports on prevailing market fraud rate information to their users.

Perceived risk is a measure of buyers’ perception of risk. It has been used as a mediating variable in past studies (e.g. [47]). We could find a significant effect only of sellers’ reputations on perceived risk and not that of buyers’ risk attitudes. Apparently, the absoluteness of information about the market, such as trader reputation, product price, and expected net benefit, led to the subjects relying less on their risk instincts. We believe this is a useful and important finding. The Market Factors Model provides a stronger Goodness of fit measure than the Perceived Risk Factors Model. Based on the data and the analysis, we can conclude that reputation, price, and fraud rate explain OES adoption behavior better than personal factors such as perceived risk.

Interestingly, the effect of being defrauded was not significant in OES adoption behavior. There are a couple of reasons for this counter-intuitive finding. First, the cheating instances were introduced at random and not at pre-specified points in time. Some subjects were cheated early in the session, and some were cheated later in the session. Thus, the number of transactions before being cheated and the number of transactions after being cheated were not comparable between subjects. Second, the cheats might have resulted in relatively small losses, and thus may not have affected subjects’ net earning significantly. The effects of these variables will have to be studied in isolation of other factors, and this can be a potential future study.

We used student subjects as proxies to real traders on the Internet. We believe that the sample is quite representative of a certain segment of the population of active buyers on the Internet. However, there are other types of buyer groups as well. It is important to study

<table>
<thead>
<tr>
<th>Variables manipulation</th>
<th>Change in probability</th>
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<tbody>
<tr>
<td>Price change (low to high)</td>
<td>0.038</td>
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<tr>
<td>Fraud rate change (from low to high)</td>
<td>0.037</td>
</tr>
<tr>
<td>Reputation change (mean to mean -1)</td>
<td>0.011</td>
</tr>
<tr>
<td>Reputation change (mean to mean +1)</td>
<td>-0.011</td>
</tr>
<tr>
<td>Reputation change (mean to 0)</td>
<td>0.330</td>
</tr>
</tbody>
</table>

Table 8

Sensitivity analysis for the market factors model
the behavior of other user segments, since the risk behavior of, say, a college student is different from that of a high school teacher [50]. Each subject was allocated the same amount of virtual money, and each was well motivated to maximize the cumulative net benefit. We believe that the attractive monetary prizes would have provided sufficient motivation. We considered only online escrow as a risk-relief service. The applicability of these findings to other risk-relief services would warrant closer scrutiny.

There are also some implications for electronic commerce businesses. Reporting on the reputations of sellers is important for both risk-seeking and risk-averse buyers. It can be assumed that businesses are aware of the different fraud rates for different market segments. They can have a dynamic mechanism for pricing OES products, thereby attracting more buyers for their products than before. For example, for low fraud rate markets, businesses can charge low OES fees, and for high fraud rate markets, higher OES fees. In addition, the relationship between reputation scores and OES adoption can be used by practitioners to fine-tune their business strategies.

The significant correlations between expected utility and decision behavior can be interpreted as supporting rational behavior of the subjects. It is likely that the decision behavior was more in accordance with rational behavior and less based on instincts. A number of additional research questions can be considered. What are the effects of artifacts such as budgetary constraints and time constraints on OES adoption decisions? It has been reported that risk behavior is affected by the frequency of information reporting [46]. Typically, the OES selection support shown in Fig. 2 is not present in a real online auction. Therefore, it would be interesting to study how much an impact this additional support system has on OES adoption. The OES selection system reports the account balance information after each transaction. It would be interesting to study whether buyers’ behavior changes if risk reporting is less frequent.

In this study, we set out to explore the factors that affect OES adoption. We found that traders’ fraud rate, price of the product, and reputation were to be significant factors. We also found that traders’ reputations are a good explanatory variable for perceived risk and subsequently for OES adoption behavior. We found no effect of cheating on OES adoption or risk attitude on perceived risk. The findings of this study can be useful to online escrow service providers and researchers of auction system users’ behavior. We conclude by stating that this is the first such empirical study and that there are many more interesting research questions to be answered.

Appendix A. Risk attitude questionnaire

<table>
<thead>
<tr>
<th>Choice A</th>
<th>Choice B</th>
<th>Circle one</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) 50% chance of winning $450 for sure</td>
<td>$1000</td>
<td>A B</td>
</tr>
<tr>
<td>2) 80% chance of winning $3000 for sure</td>
<td>$4000</td>
<td>A B</td>
</tr>
<tr>
<td>3) 80% chance of losing $4000</td>
<td>Losing $3000 for sure</td>
<td>A B</td>
</tr>
<tr>
<td>4) 20% chance of losing $4000 25% chance of losing $3000</td>
<td>A B</td>
<td></td>
</tr>
<tr>
<td>5) 20% chance of losing $4000</td>
<td>25% chance of losing $3000</td>
<td>A B</td>
</tr>
<tr>
<td>6) 45% chance of winning 90% chance of winning</td>
<td>$6000</td>
<td>$3000</td>
</tr>
<tr>
<td>7) 10% chance of winning $100 for sure</td>
<td>$1000</td>
<td>A B</td>
</tr>
<tr>
<td>8) 10% chance of losing $1000</td>
<td>Losing $100 for sure</td>
<td>A B</td>
</tr>
</tbody>
</table>

Coding scheme: $A = 0$, risk-seeking; $B = 1$, risk-averse. If a trader’s scores $< 4$ the trader is risk-seeking; otherwise, he is risk-averse.

Appendix B. Main features of the C2C auction simulation system

The C2C auction simulation system can reproduce a whole process of C2C auction with online escrow services, which includes the following functions:

- Merchandise posting,
- Bidding,
- Contracting,
- Risk assessing,
- Honest trader’s OES adoption decision-making,
- Cheater’s fraud decision-making, and
- Transaction auditing.

Typically, the simulation system accomplishes the following main tasks in a run:

- Randomization of the following parameters during each trade:
  - The item to be sold, which is a specific merchandise chosen from a set of products;
  - The number of buyers bidding for the item;
  - The perceived values of underlying product for buyer and seller;
  - The winning price;
  - Trader’s reputation;
  - PRR calculation parameters;
  - A trading partner’s type, either an honest one or a defrauding one, with regard to a trader’s reputation score.
• Recursive calculation of base PRR and dynamic PRR.
• Assessment of the fraud status and OES status after each transaction.
• Dynamic data collection.

References


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