

ANALYSIS OF SUCCESSFUL TRADES INFORMATION DISCLOSURE MECHANISM

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Abstract. In most of e-commerce sites evaluation systems are employed to evaluate each user after trades. Normally, seller's evaluation score is shown in e-commerce site and computed based on the score given by buyers. In recent e-commerce sites, the evaluation is based on multiple attributes and buyers give their thinking for each attribute. In this viewpoint, the seller evaluation in e-commerce is collected knowledge from buyers and the synthetic score is computational intelligence because each buyer makes his/her decision whether he/she trades with the seller. In this paper, we discuss the computational intelligence of the evaluation system in e-commerce. Then, to avoid asymmetric and incomplete information in trades, we design a mechanism of the trader evaluation. After that, we present some experiments to show the rate of successful trades in our proposed mechanism. Contributions of this paper are showing the theoretical discussion of e-commerce computational intelligence, design of evaluation mechanism and the effectiveness of the proposed mechanism.

Keywords: Electronic commerce, computational intelligence, information disclosure, mechanism design, evaluation systems

1 INTRODUCTION

Computational intelligence is a form of information that is organized by a bottom-up information. Some of them are useful and practical when people make decisions. In the recent years, computational collective intelligence has appeared on the web and helps users to make their decisions. Particularly, trading evaluation is the

collected knowledge from users to evaluate traders. It provides the characteristics of sellers based on a multi-attribute evaluation criteria. As the online market size develops, the number of crimes and frauds on the internet has been increasing year by year. Generally, electronic commerce site provides the seller rating function in order to disclose the seller's information [3]. Evaluation systems in electronic marketplaces are strong functions to make a successful trade and to provide safe and secure trading. Even if the e-commerce site uses a simple evaluation system, the evaluation system is effective enough to avoid dishonest behavior [4]. The existing evaluation system has a strong limitation aspect that users input their rating on unified evaluation attributes. Criteria to be evaluated are also not defined in the existing evaluation systems. Sellers provide incomplete/incorrect information on an e-commerce website, buyers cannot make a final statement based on the seller rating system. In some cases, there is a lot of asymmetric information between buyers and sellers.

To solve the above mentioned problems in e-commerce and the evaluation systems, we propose a new evaluation method in which sellers disclose a lot of trustworthy information. In our method, sellers can freely choose evaluation attributes that are important for the sellers to deal. Evaluation for seller determines the synthetic evaluation based on number of the attributes. Namely, the total evaluated score depends on the number of evaluation items. If the seller provides many evaluation items, our model gives extra points for the seller. When a seller provides a lot of evaluated information even though each score is not so high, buyers may consider such seller as a creditable seller. This means a seller has an incentive to disclose his/her information on the evaluation system as much as possible. Thus, the seller has an incentive to set more evaluation items that are evaluated by buyers. Latter in this paper we provide the result of our experiment to clarify the feature of our model and give some discussion regarding a seller's strategy.

Contributions of our paper are

1. clarifying evaluation mechanism to promote information disclosure,
2. proving that a seller has a high successful trade providing a lot of attributes except for the situation where a buyer gives high rating on less attributes, and
3. discussing seller's best strategy under both models and also actual buyer's preferences.

In Section 2, we explain what is the collective intelligence in e-commerce. In Section 3, we explain incomplete information in e-commerce and introduce existing evaluation systems and some related work. Then, in Section 4, we propose a novel evaluation model based on the number of displayed information. Section 5 presents experiments using real data regarding buyer's preferences and discusses seller's strategy in each experiment case. Finally, we summarize our study and outline our future work in Section 6.

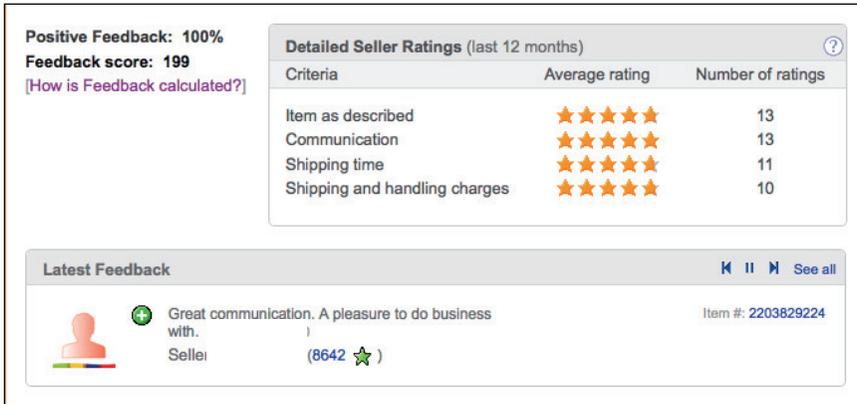


Figure 1. Evaluation system in e-commerce

2 E-COMMERCE COLLECTIVE INTELLIGENCE

2.1 Trader Evaluation System

In the evaluation system of e-commerce, we can view a lot of useful information input from the past traders. When a seller’s evaluation score is not high, you may not trade with him/her. When you want to get an item as quickly as possible, you may focus on the attribute about speedy delivery rather than a total score. Each score is generally calculated as an average of given scores from past buyers. Also, a total synthetic score is the average of score of each attribute. Namely, we can identify the collective intelligence in the evaluation system of e-commerce. Statically, as the number of sample data increases, the reliability is increased as well.

However, the total score does not reflect the characteristics of sellers. And also, it does not clarify the trading history because items have different features if the category is not the same. In next subsection, we show an example where evaluation scores cannot be compared if the items are categorized in different categories.

2.2 Undifferential Evaluations

Consider when you buy a food in the internet shopping site. You may think about the speedy delivery when you buy a fresh food like meat. On the other hand, when you buy a motorcycle, you may think about a detailed information in addition to multi-attribute evaluation criteria. Also, you may think whether the trader is trustworthy or not. When you buy an electronic device, you may think about the country in which the device was made in addition to the brand. In this condition, the common evaluation criteria should not be used. There is a specific evaluation attribute for each category.

2.3 E-Commerce Computational Collective Intelligence

In traditional evaluation system, its method to show the result of evaluation is quite simple because the evaluation attributes are fixed [18]. However, as shown in the above subsection, each category has some special feature to be evaluated. Also, the number of evaluation attributes is different between the categories. However, it is not easy to decide on the criteria of evaluation. To solve the problem, we propose a novel method of evaluation in e-commerce. The outline of the method is shown in the Figures 2 and 3. First, the seller decides on the evaluation attributes. Then, buyers evaluate sellers on the attribute. When the seller is evaluated by a buyer, the evaluation criteria are determined clearly. In this process, the evaluation score is adjusted by our proposed controlled value. Using our method, sellers have the incentive to disclose the information as much as possible. Also, the sellers have the incentive to make their trading carefully.

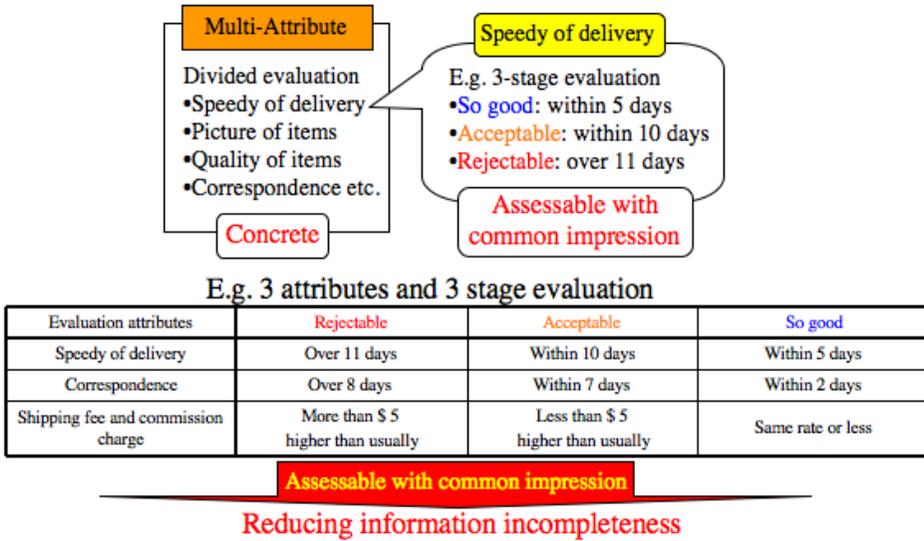


Figure 2. Evaluation criteria

3 PRELIMINARY DISCUSSIONS

3.1 Incomplete Information

In the internet-based shopping, buyers view items information and sellers information based only on displayed information found by the web browser. Buyers cannot perfectly learn about the actual information from the internet until they receive

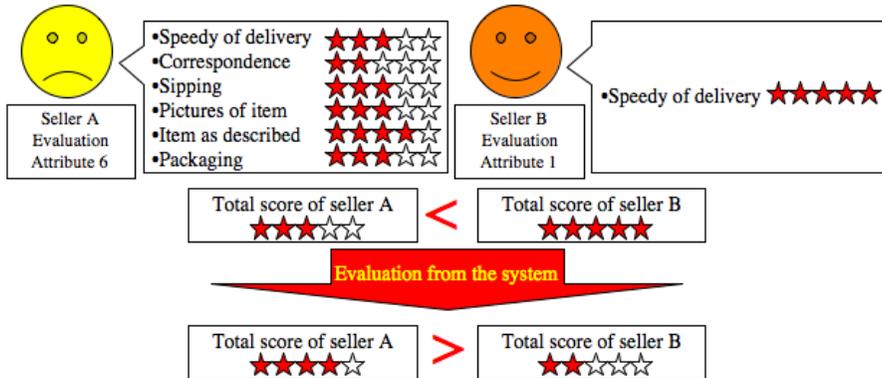


Figure 3. Concept of computational collective evaluation knowledge

purchased items. These situations put out incomplete information, like every existing electronic commerce web site. In an e-marketplace, differences in the quantity and quality of information between sellers and buyers are a big issue for both sides. These situations highlighted the problem on the asymmetric information. Web-based marketplace has more asymmetric information than actual marketplaces. In the actual marketplaces, buyers can view items from multiple aspects, sometimes touch and pick them up. Thus, they can make sure about the material, quality, size, and several other informations. On the other hand, when users try to buy items on the electronic marketplace, they cannot touch and pick items up. Further, they just look at some pictures taken by sellers. Some sellers are in a good faith and honest, but others may hide or trim the provided information. It makes unfair trades. It is very important for buyers that there is no information gap between them and sellers. Unfair issues on the trades cause that buyers sometimes fail in their decision making to select items. This means that buyers' utilities are decreased by providing the unfair information.

3.2 Existing Evaluation Systems

Yahoo! [6], Rakuten [7] and amazon.co.jp [8] are popular e-commerce sites in Japan. In their system, users can input their evaluation including a total/synthetic evaluation and evaluation by free description. Users can find out the latest result of evaluation and to make decision by viewing whether a trading partner is active or not. In addition, the overall rating has no clear criteria and trends to be evaluated according to buyer's subjective opinion. Although the existing evaluation systems have these features, buyers can never get a perfect information about sellers and items with the incomplete and asymmetric information. A lot of causes of criminal acts are set up by the information problems.

3.3 Evaluation Differences

Difference of evaluation among sellers affects each buyer's decision making in the online auction. For example, we consider a situation where a buyer tries to buy an item. When there are two seller candidates who deal in the same item on the same price, the buyer would purchase the item from a seller whose evaluation point is higher. This means the difference of a total utility and risk affecting the buyer's decision making. Even though there is a price difference between each seller's item, the buyer rationally chooses the trading partner based on the risk. Let us suppose the total utility is indicated as U and it consists of price P and degree of risk R based on integration function F . Total utility for first item and seller shows $U_1 = F(P_1, R_1)$. Total utility for second item and seller shows $U_2 = F(P_2, R_2)$. Buyer would make decision based on the difference between U_1 and U_2 rather than on each difference between P_1 and P_2 , and between R_1 and R_2 . Thus, the buyer sometimes does not look at the web site if the seller's evaluation score is rather low.

3.4 Related Work

A research on the evaluation system in online auction system is very popular and a lot of contributions are published [10]. Kobayashi analyzed the evaluation mechanism on the internet auctions considering its network structure, that is, the relationship between buyers and sellers [9]. His contribution proposes a new evaluation model of network structure instead of the evaluation on trades by sellers and buyers. Further, in the contribution [10], he implemented the evaluation system with the evaluation algorithm of a web page. He also analyzed it through experiments to make sure about the effectiveness of the approach.

Ming analyzed the evaluation method of online auction to take in exponential smoothing [11]. It was analyzed to avoid the cheating because a bad evaluation has a big impact on seller's evaluation to give a lot of weight to the last evaluation. It is a great effect and it is an important tool for the buyer in identifying the seller's cheating or unfair behavior in the trade.

Shanshank analyzed the method employing a probabilistic reasoning to extract discriminative and sketchy traders in internet auction [12].

Fasanghari analyzed the evaluation method to investigate a real customer satisfaction based on fuzzy logic in online commerce [13].

Usui showed that the evaluation system affects the importance on the market revitalization by comparing the existence or nonexistence of evaluation system [1, 5].

Yamamoto analyzed users behavior information through actual experiments with test subjects in the internet auctions [14]. He also analyzed important information for users in the auction.

Ito analyzed the internet auction protocol to permit the Pareto efficient distribution [15]. It shows that the protocol can add measures according to which the goods quality can be checked and a honest declaration by a specialist can be made

when there are a lot of asymmetric information and some specialist in the Internet auction.

However, most of them do not mention the secure mechanism design of the evaluation system to avoid incomplete and asymmetric information.

4 EVALUATION MODEL

In this section, we propose a new objective evaluation model based on quality and quantity of disclosure of information. First, we put and attach the concept of criteria to evaluate. In existing evaluation systems, users are sometimes confused because of no criteria for evaluation. For example, popular e-commerce sites provide only synthetic evaluation. Some other sites provide multiple attributes to evaluate like “Speedy deliver”, “Politeness to customers”, and several others. However, how do sellers gain a good evaluation about “Speedy deliver”? How do sellers get a positive score about “Attitude to buyers”? Even though a seller does use the same attitude in helping and taking care of the customer, each evaluation from buyer would be different. Thus, to make more useful information, our proposed evaluation system sets concrete criteria. Further, we set an incentive model for sellers to grow and improve their trading skills.

4.1 Model

- Evaluation index for sellers in the evaluation by buyers is defined as $I = \{1, 2, \dots, i, \dots, n\}$.
- Impression value $A = \{\alpha_1, \alpha_2, \dots, \alpha_i, \dots, \alpha_n\}$ is defined as an impression when a buyer looks at the item’s information on the e-commerce site.
- Impression value $B = \{\beta_1, \beta_2, \dots, \beta_i, \dots, \beta_n\}$ is defined as an impression after a buyer received the item.

When the attribute is $\alpha_i = \beta_i$, buyer’s impressions are the same on the item information on the web and the fresh information. When the attribute is $\alpha_i > \beta_i$, buyer’s impression at the item browsing is better than the impression after he/she received the item. When the attribute is $\alpha_i < \beta_i$, buyer’s impression at the item browsing is not better than the impression after he/she received the item.

4.2 Evaluation from Trading Partners

Even though an expression value and the item information value are the same, sensitivity and feeling of the explanation and introduction of items are different for each buyer. When evaluations are given using a stage assessment model, each buyer evaluates based on his/her multiple scale. To avoid such dispersion, we set a criterion for each evaluation attribute. For example, when the delivered item is evaluated on

the sameness between the actual item and the picture shown at the e-commerce site, we give a certain criterion like shown in Table 1. The adjusted values of important criteria are higher and the values of unimportant criteria are lower. The values can be changed by the e-commerce site manager.

Criteria	Rate
Delivered item is same with the picture on the web	1.5
Actual item's size is same with the description on the web	1.3
⋮	

Table 1. Example of criteria and adjusted values

We consider the case when a seller deals in a brand-new item. When delivered item is without any scuff and it is perfectly the same with the picture on the web site, buyers must evaluate “so good” and give 3 points. When the item has a small scuff, buyers evaluate “acceptable” and give 2 points. When the item has a dent or chippage, buyers evaluate “rejectable” and give 1 point. When the item is not delivered, buyers evaluate “Hopeless case” and do not add any points. We give another example about delivery. When the item is delivered in 3 days after the payment, buyers must evaluate “so good” and give 3 points. When the item is delivered in 7 days after the payment, buyers evaluate “acceptable” and give 2 points. When the item is delivered in 14 days after the payment, buyers evaluate “non-desirable” and give 1 point. When the item is not delivered, buyers evaluate “Hopeless case” and do not add any points.

On the other hand, when a seller deals in the used item and delivers to overseas, the evaluation attribute becomes different from the above mentioned examples. When delivered item is perfectly the same with the explanation on the web site, buyers must evaluate “so good” and give 3 points. When the item is more suspicious than the explanation, buyers evaluate “acceptable” and give 2 points. When the item has a serious defect without any explanation, buyers evaluate “rejectable” and give 1 point. When the item is not delivered, buyers evaluate “Hopeless case” and do not add any points.

Thus, incomplete information are reduced by these evaluations based on comparison between actual things and criteria. If a lot of buyers evaluate attributes in which the original item is different from the picture on the web in the past, the seller is known as a person who does not deal in the acceptable item. Our proposed model provides more concrete information comparing it with the existing e-commerce sites.

4.3 Evaluation from the System

4.3.1 Information Disclosure

Our proposed model is based on number of information disclosure. Multiple attributes to evaluate are prepared and a seller selects attributes based on his/her

strengths. If he/she is good at packing, he/she can choose the “Package” as the evaluated attribute. On the other hand, if he/she does not want to disclose his weakness, he/she can omit the attribute to be evaluated. To design a desirable mechanism in evaluation, we set a control value based on number of information disclosure. When a seller changes five attributes from four attributes to be evaluated, the system gives an incentive points to the seller. Namely, if the seller discloses more attributes, the incentive points are given in proportion. Thus, he/she sets up a lot of attributes to get many incentive points. And also, incomplete information are reduced from the shopping site. However, if he/she does so, he/she needs to be careful in each activity on the trade.

If a seller provides an item’s information by pictures and explanation, a risk on the trade is decreased [16, 17].

4.3.2 Accumulative Extra Point

Here, we define an experience value based on the accumulative number of trades for each hotel. In existing evaluation systems, the score/rating of evaluation is calculated simple accumulative trading experience. For example, when a hotel has 30 positive rating without any negative rating and he/she gets a positive rating in a subsequent trade, his/her score rating is 31. However, we propose an appreciate model for outstanding hotels. The outline of the model is that the system gives an extra point for a hotel which continues a lot of trading without negative rating from travelers. On the other hand, once he/she gets a negative point, the accumulative number goes back to the start. For example, when a hotel has accumulative positive rating 100 without any negative rating and he/she gets a positive rating in a subsequent trade, the system gives an extra score automatically. Thus, the marketplace positions outstanding hotels apart from the rest hotels.

A number of successful continuous trading $D_{i_k, h_l}^{c_j}$ is decided by the number of trading. If the hotel gets a good rating continuously, the value γ increases. The value $D_{i_k, h_l}^{c_j}$ is based on the number of successful trades of k^{th} attribute on l^{th} trading.

We show the algorithm considering the evaluation from the system about the number of successful continuous trading $D_{i_k, h_l}^{c_j}$. The rate of increasing the number of successful continuous trading $D_{i_k, h_l}^{c_j}$ is γ . If the hotel gets good evaluations continuously, γ increases. Otherwise, γ is reduced. If the hotel has a negative evaluation after a lot of good evaluations, added point becomes D_{i_k, h_l}^c that is excluded γ . Namely, the accumulative point $D_{i_k, h_l}^{c_j}$ is reset by the system. When users give the neutral evaluation $e_{i_k, h_l}^{c_j} = 0$, the value $D_{i_k, h_l}^{c_j}$ also is reset.

In our model, we are showing the range of the evaluation as $-1, 0$, and 1 .

```

begin
  for  $j \leftarrow 1$  step 1 to  $n$  do
    for  $l \leftarrow 1$  step 1 to  $o$  do
      for  $k \leftarrow 1$  step 1 to  $m$  do
        if  $e_{i_k, h_l}^{c_j} > 0$  then begin
          if  $e_{i_k, h_{l-1}}^{c_j} > 0$  then begin
             $D_{i_k, h_l}^{c_j} \leftarrow D_{i_k, h_l}^{c_j} + \gamma;$ 
             $e_{i_k, h_l}^{c_j} \leftarrow e_{i_k, h_l}^{c_j} + D_{i_k, h_l}^{c_j};$ 
          end
        end
        else if  $e_{i_k, h_l}^{c_j} < 0$  then begin
          if  $e_{i_k, h_{l-1}}^{c_j} > 0$  then begin
             $D_{i_k, h_l}^{c_j} \leftarrow D_{i_k, h_l}^{c_j} + \gamma;$ 
             $e_{i_k, h_l}^{c_j} \leftarrow e_{i_k, h_l}^{c_j} - D_{i_k, h_l}^{c_j};$ 
             $D_{i_k, h_l}^{c_j} \leftarrow 0;$ 
          end
          else if  $e_{i_k, h_{l-1}}^{c_j} < 0$  then begin
             $D_{i_k, h_l}^{c_j} \leftarrow D_{i_k, h_l}^{c_j} - \gamma;$ 
             $e_{i_k, h_l}^{c_j} \leftarrow e_{i_k, h_l}^{c_j} + D_{i_k, h_l}^{c_j};$ 
          end
        end
        else begin
           $D_{i_k, h_l}^{c_j} \leftarrow 0;$ 
        end
      end
    end
  end
end
end
end

```

Question (1): Which do you have prefer buying in e-commerce, products low prices, high seller's rating or both low price and high evaluation?				
Priority	Item Price	Evaluation	Both	Others
Totals Num.	13	4	39	1

Table 2. Questionnaire result (1)

5 EXPERIMENTS

We conducted experiments to measure our proposed model. When the system changed the evaluation depending on the number of evaluation attributes, we searched the market conditions where buyer can have dealings with confidence. In the market conditions, we configured

Question (2): When there are variety sellers disclosing some evaluation attributes between one to ten, how many is your desirable number of evaluation attributes?										
Attributes Num.	1	2	3	4	5	6	7	8	9	10
Totals Num.	3	0	5	5	20	10	3	5	0	6

Table 3. Questionnaire result (2)

1. Buyer takes precedence elements in dealing,
2. Buyer has an impression to concern the evaluation for seller when buyer looks at multiple attributes,
3. About the number of each buyer type defined by 1. and 2.

In the definition of 1., the experiments assumed three buyer types including price-oriented (PO), evaluation-oriented (EO), and neutral buyers (N) in the marketplace. Price-oriented buyers prefer a low price item rather than rating of evaluation to decide a seller to trade. Evaluation-oriented buyers have a trend to choose sellers with rating of evaluation rather than item’s price. Neutral buyers have both above features. In the definition of 2., we set that buyer has a good impression on the specific number of evaluation attributes and gives seller one level higher rating. In the definition of 3., we investigated how many buyer types are defined because we did not know whether it exists in the actual marketplace.

5.1 Survey

We made a survey with fifty-seven people for order to set parameters for our experiments. We asked two questions.

Question (1): Which do you prefer when buying the item in e-commerce: low prices, high seller’s rating or both low price and high evaluation?

Question (2): When there are various sellers disclosing some evaluation attributes between one to ten, how many evaluation attributes are desirable for you?

Table 2 shows the questionnaire result regarding buyer’s preference in online market. From questioner’s answer in the question (1), most of them are interested in both low price items and high evaluation sellers. And there are few questioners who make a point of only high evaluation of the seller. Table 3 shows the questionnaire result regarding buyer’s impression about number of evaluation attributes. From questioner’s answer in the question (2), many questioners prefer around five evaluation attributes. Result in the question (2) looks like a normal probability distribution between one and ten. Into the experiments we involved the distribution of each buyer type received from the above result.

5.2 Setting

In the marketplace, rating of evaluation is rated through 1 to 5 of integers. Item’s price is assumed between \$400 and \$600 chosen by a normal distribution on distribution value 50. The average of price of sold items is \$500. We assume three types of buyers preferences. First, if the buyer has the preference about price of item, the threshold of decision-making D_p is shown as Equation (1). If P_s is larger than the equation, buyer trades with a seller who deals in at the lowest price out of candidates.

$$D_p : p - \frac{e}{10} \tag{1}$$

Second, if the buyer has the preference about seller’s evaluation, the threshold of decision-making D_e is shown as Equation (2). If E_s is larger than the equation, buyer trades with a seller who deals in at the highest rating out of candidates.

$$D_e : \frac{500 - p}{10} + e \tag{2}$$

Third, if buyer is neutral about the price and seller’s evaluation, the threshold of decision-making D_n is shown as Equation (3). If $E_s/3 - P_s/500$ is larger than the equation, buyer trades with a seller who deals in at the highest value (than threshold value) out of candidates.

$$D_n : \frac{e}{3} - \frac{p}{500} \tag{3}$$

- p indicates item’s price and e indicates rating of evaluation.
- P_s indicates item’s price shown by seller.
- E_s indicates seller’s rating of evaluation.

In the setting of experiments, four types of evaluation trends are assumed with number of evaluated attributes. The number of evaluated attributes is between 1 and 10.

We assume four types of evaluation given for the seller. The following is detail of each evaluation type.

Experiments	Number of Buyer’s Type
Experiments	Case 1: PO = 100, EO = 100, N = 100, EP = 0
(A), (B),	Case 2: PO = 100, EO = 100, N = 100, EP = 1
(C), (D)	Case 3: PO = 69, EO = 21, N = 210, EP = 0
	Case 4: PO = 69, EO = 21, N = 210, EP = 1

Table 4. Experiment setting

(A) Average of evaluation value monotonically increases when the number of evaluated attributes increases.

- (B) When the number of evaluated attributes increases, the average of evaluation value increases exponentially.
- (C) When the number of evaluated attributes increases, the average of evaluation value increases with a marginal decreasing.
- (D) When the number of evaluated attributes is around 5, it tends for buyers to give high rating like in a normal distribution.

Table 5 shows types of evaluation used in experiments. Horizontal axis shows the number of evaluation attribute, vertical axis shows the distribution of average evaluation. These evaluation types include both the rating given by the buyer and the extra point from number of evaluation attributes.

Depending on characteristics of buyers, some of them give a low rate of evaluation when a seller provides a lot of evaluation attributes because the evaluating activities are not simple and make buyers bothered to fill in the form. We have considered such situation in our simulation.

Table 4 is a setting of 4 cases of experiments. Buyer’s preferences are shown as PO, EO, and N. PO indicates the buyer’s preference in which he/she has a price-oriented preference. EO indicates the preference in which he/she has an evaluation-oriented preference. N indicates a neutral buyer who has the preference both in price and evaluation. In cases 1 and 2, we assume there is the same number of types of buyers in the market. In cases 3 and 4, the rates of buyer’s preferences are respectively used from our survey result shown in Table 2. EP indicates the condition where the number of attributes effect buyer’s input to evaluate. When $EP = 0$, number of evaluation attributes are not effected in an evaluation by buyers. When $EP = 1$, some buyers give a high rate when the number of attributes to be evaluated is the same as their preferences shown in Table 3. For example, when a buyer prefers that the number of attributes is 6, he/she gives a high rate if the trader provides 6 attributes to be evaluated. In the experiment, we assume that buyer gives 1 additional rate in such case.

Results of the experiments shows the average of rate of successful trade in 1000 trials. We assume that there are three hundred potential buyers and one hundred potential sellers to trade.

	1	2	3	4	5	6	7	8	9	10
(A)	3	3.15	3.3	3.45	3.6	3.75	3.9	4.05	4.2	4.35
(B)	2.5	2.6	2.7	2.8	2.9	3.1	3.3	3.6	3.9	4.2
(C)	3	3.6	4.2	4	3.7	3.4	3.1	2.8	2.5	2.2
(D)	3	3.2	3.4	3.6	3.8	4	4.2	3.9	3.5	3

Table 5. Evaluation given seller

	1	2	3	4	5	6	7	8	9	10
Case 1	.31	.32	.35	.38	.43	.46	.50	.53	.56	.58
Case 2	.31	.32	.36	.42	.49	.50	.51	.53	.56	.59
Case 3	.30	.33	.35	.37	.41	.43	.46	.48	.49	.49
Case 4	.30	.33	.36	.41	.47	.45	.47	.48	.49	.50

Table 6. Experiment (A) result

5.3 Result of Experiment

Experiment results are shown in Tables 6 to 9. Each experiment condition respectively employed the evaluation types (A), (B), (C), and (D). Horizontal axis indicates the number of evaluation attributes, vertical axis indicates the rate of successful trade in graphs.

5.3.1 Experiment (A)

In this experiment, the type (A) in Table 5 is used as the buyers' trend. Table 6 shows the result of experiment on a setting of Experiment (A) in Table 4. When the evaluation given by buyers and by the system is high, the successful trade rate is also high in the marketplace. When each buyer type exists respectively the same rate, the transaction success rate is flat in the number of each evaluation attribute. On the other hand, when we employ a condition of cases 3 and 4, the successful trade rate is high when the number of evaluation attributes is between 5 and 10. This means that the seller's best strategy is to define 5 or more attributes to be evaluated.

5.3.2 Experiment (B)

In this experiment, the type (B) in Table 5 is used as the buyers' trend. Table 7 shows the experiment result on a setting of Experiment (B) in Table 4. When the average of the evaluations given by buyers and by the system is three or less (see the type (B) in Table 5), effect of the impression value is low. In cases 3 and 4, the rate of successful trade is extremely low. The best strategy for sellers is to provide a lot of attributes to be evaluated.

5.3.3 Experiment (C)

In this experiment, the type (C) in Table 5 is used as the buyers' trend. Table 8 shows the experiment result on a setting of Experiment (C) in Table 4. The successful trade is high on the number of evaluation attributes between 3 and 5. On the other hand, in cases 3 and 4, the number of successful trades is quite low on the number of evaluation attributes between 7 and 10. This means that the seller's best strategy is to prepare 4 attributes or around 4 to be evaluated. Only this result shows that the seller should not provide more than 5 evaluation attributes.

5.3.4 Experiment (D)

In this experiment, the type (D) in Table 5 is used as the buyers' trend. Table 9 shows the experiment result on a setting of Experiment (D) in Table 4. In the Cases 1 and 2, successful trades are the highest between 5 and 8. Considering actual trades, the seller's best strategy is to define attributes between 6 and 7 to be evaluated.

	1	2	3	4	5	6	7	8	9	10
Case 1	.27	.27	.28	.29	.30	.32	.35	.42	.50	.56
Case 2	.27	.27	.28	.30	.32	.34	.36	.43	.50	.56
Case 3	.23	.25	.26	.28	.29	.32	.35	.41	.46	.49
Case 4	.23	.25	.26	.28	.33	.33	.36	.40	.46	.49

Table 7. Experiment (B) result

	1	2	3	4	5	6	7	8	9	10
Case 1	.31	.43	.56	.52	.45	.38	.32	.29	.26	.26
Case 2	.31	.42	.57	.54	.51	.42	.32	.29	.27	.26
Case 3	.30	.41	.49	.47	.42	.37	.32	.28	.23	.21
Case 4	.31	.41	.49	.48	.47	.41	.33	.28	.23	.21

Table 8. Experiment (C) result

	1	2	3	4	5	6	7	8	9	10
Case 1	.31	.33	.37	.43	.48	.52	.56	.50	.40	.31
Case 2	.31	.33	.38	.45	.54	.55	.56	.50	.40	.31
Case 3	.30	.33	.37	.41	.44	.47	.49	.46	.39	.30
Case 4	.30	.33	.39	.43	.48	.48	.49	.47	.39	.31

Table 9. Experiment (D) result

6 CONCLUSION

In this paper, we designed the evaluation model in which sellers have an incentive to disclose a lot of information about the item and about themselves. Except for the situation where buyers do not want to evaluate a lot of attributes, the seller can get highly successful trades if he/she provides 4 or more attributes. By using our proposed method, users evaluate sellers more precisely because our method provides concrete criteria to be evaluated. Our model is based on a multiple attribute evaluation including evaluation from the buyer and the system. System gives an extra point based on the number of evaluation attributes set by sellers. Even though a seller is good at packaging, the system discounts the rating as a penalty when

he/she chooses only one attribute “packaging” as a detailed rating. Our model is efficient to promote information disclosure, to reduce incomplete, and to decrease asymmetric information.

Our future work includes analyses and modeling of situations where buyer’s preferences to evaluate are changing dynamically.

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