DEA 방법론을 이용한 온라인 판매자 추천 시스템의 구축

How to Recommend Online Shopping Consumers the Best of Many Sellers? : Online Seller Recommendation System Using DEA Method

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초 록

구매자와 판매자의 판매과정에서 '구매가치'는 구매자의 구매의사결정에 있어서 매우 중요한 가격대비 질의 중요한 측정치이다. 본 논문의 목적은 온라인 구매자들이 동일한 물건을 파는 판매자들 중에 최적 판매자를 선택하는 데 도움이 되는 방법론을 제안함에 있다. 이 방법론 수립을 위하여 DEA(data envelopment analysis) 방법론의 적용모형의 하나인 FDH (free disposal hull) 모형을 사용하고, 이 모형의 유효성을 실제 가격비교 사이트로부터 획득한 데이터를 이용하여 검증하였다.

모형 검증과정에서는 가격, 브랜드, 배달 기간 등 거래 조건에 대하여 구매자들이 어떻게 반응하는지를 우선 분석하고, 이를 바탕으로 구매자의 구매 의사결정을 돕는 판매자 추천 시스템을 구축하였다. 본 연구를 통하여 검증된 FDH 모형은, 구매자 측면에서 최적조건, 최저가로 좋은 제품과 서비스를 원하는 구매자에게 유용한 정보를 제공하고, 나아가 자동화된 소규모 거래에도 활용될 수 있을 것으로 기대된다. 판매자 측면에서는, 구매자의 선호도를 더욱 자세히 파악함으로써 타판매자 대비 경쟁력을 가지는 벤치마킹 전략을 수립하는 데에도 유용하게 이용될 수 있을 것으로 기대된다.

ABSTRACT

In a buyer-seller transaction process, 'value for money,' a measure of quality-price ratio, is one of the most important criteria for buyers' purchasing decisions. The purpose of this paper is to suggest a method which helps online shoppers choose the best of several sellers offering homogeneous goods. We suggest FDH (free disposal hull) model, an applied model of data envelopment analysis (DEA), for online buyer-seller transactions and verify it with the data from an Internet comparison shopping site.

For this purpose, we analyze consumer choice behaviors by examining how consumers respond to different sale conditions such as price, brand, or delivery time. Then, we implement a seller recommendation system to support buyers' purchasing decisions. We expect our FDH model to provide valuable information for rational buyers who want to

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pay the least price for high quality products/services and to be used in implementing automated evaluation processes in micro transactions. Moreover, we expect that our results can be utilized for sellers' benchmarking strategies which help sellers be more competitive by showing them how to attract buyers.

키워드 : 비교쇼핑, 가격비교, 판매자 추천, DEA(Data Envelopment Analysis), FDH(Free Disposal Hull)
Comparison Shopping, Price Comparison, Seller Recommendation, Data Envelopment Analysis, Free Disposal Hull

1. Introduction

When purchasing a specific book or an MP3 player, buyers on online shopping try to select the best of several sellers offering homogeneous goods with different sale conditions, such as price, delivery time, and customer service. In doing so, they desire to select the seller which can obtain the highest satisfaction for what they pay. Actually, many consumers consider quality-price-ratio in order to choose a 'best-buy' [18]. Recently, an increasing number of consumers are visiting Internet comparative shopping services, which are referred as shopbots (short for shopping robots) in Smith and Brynjolfsson [17] and Montgomery et al. [14].

Typically, shopbots display a comparative information on a variety of sellers and rank the sellers based on the characteristics of interest to the buyer such as price, delivery time, or customer satisfaction scores. A few shopbots provide a recommendation information through a customer certified mark or trust store mark. Such a recommendation mark is granted to the seller receiving a higher evaluation score. Some of them, such as the 'BizRate,' 'DealTime,' 'Shopping Smart,' 'Shopzilla,' and 'Epinions,' provide the 'best buy' mark to the seller presenting the least cost among the recommended sellers. However, most consumers cannot easily make a purchasing decision with such recommendation marks, which do not reflect quality-price-ratio.

In a buyer-seller transaction process, 'value for money,' a measure of quality-price-ratio, is one of the most important criteria for a buyer- purchasing decision [16]. The terms 'value' and 'money' represent a composite measure of what a buyer receives from goods and/or services and a measure of what he/she pays for them, respectively. The purpose of this paper is to help an online shopper choose the best of several sellers offering homogeneous goods. To do, we address the following problems : what affects an online shopper to choose one of several sellers offering homogeneous goods? For example, does a buyer select a seller offering the highest value-for-money rather than the lowest price? We analyze consumer choice behavior by revealing how consumers respond to different aspects of sale conditions such as price, brand and delivery time with shopbot data used by Smith and Brynjolfsson [17]. Shopbots can be utilized as a laboratory where consumers respond to heterogeneous offers from several sellers [3].

While Smith and Brynjolfsson- study [17] is one of the first empirical studies on consumer- decision-making at shopbot, Montgomery et al.- [14] is one of the first papers discussing the implementation of shopbots. They design a shopbot by developing a utility model of consumer purchasing behavior. Then they show how to reduce time-consuming searches that provide redundant or dominated alternatives. However, their implementation has a problem with measuring user preference, because their shopbot should estimate the parameters of utility model for each customer. Then it is very difficult to use this method in practice for real recommendation because of heavy load to servers in calculating and memorizing differences of customers. To solve this problem, we use one of DEA (data envelopment analysis) methods to implement shopbot.

Usually, DEA has been used to evaluate the performance of production/operation process of organizations which use inputs to produce outputs. Since DEA cross compares the combination of inputs and outputs, which are given, it does not need to assume any specific function or parameters. We suggest that a buyer-seller transaction process can be interpreted as a production process consisting of the combination of inputs and outputs, since a consumer pays the price and obtains the value from the characteristics of a product or a seller. As a result, the value for-money in transaction process is equivalent to the efficiency of the production process consisting inputs and outputs. In this view point, we implement a seller recommendation service, by measuring the value-for-money of several sellers providing the identical product with the different sale conditions.

Our study complements recent DEA studies that evaluate sellers in terms of purchase efficiency [10, 25, 26, 27, 21, 22, 28, 23]. These studies deal with heterogeneous goods or service in a traditional (off-line) transaction between a consumer and a seller. Therefore, their studies are related with goods selection in off-line shopping. In contrast, this research deals with seller selection in an online transaction process between a buyer and several sellers offering homogeneous goods.

We suggest FDH (free disposal hull) model, a DEA model, which can reflect the characteristic of a buyer-seller transaction to measure the purchase value. Then, we compare our result from FDH model with those from CCR (Charnes, Cooper, and Rhodes), BCC (Banker, Charnes, and Cooper), and hedonic pricing models. After verifying our FDH model with shopbot data, we implement a seller recommendation system. Finally, we provide sellers with benchmarking strategies which can be utilized as polices for price and service management.

2. Literature Review

2.1 Methodology Measuring Value-for-Money

In the market of the competitive goods and service, value-for-money is the general standard used for the superior purchase [16]. Value-for-money has been considered as the standard of the customer selection in many studies [15, 7, 18, 16, 19] where value-for-money is referred to consumer value, product efficiency, or purchase efficiency. In this research, we call it as value-for-money.

The choice problem of a product or a seller belongs to MCDM (multiple-criteria decision-making) which considers the various properties of a product or a seller. The problems of MCDA can be solved by MAUT (multi attribute utility theory) or Lancaster [11]'s characteristics value theory [9]. MAUT applies the same weighted value to all estimated-targets regardless of group under evaluation. On the other hand, the weighted values in Lancaster [11] are determined by the attributes of the group under evaluation.

In economics, the techniques measuring the purchase value based on Lancaster's consumer selection theory can be divided into two groups according to the method for estimating the empirical production function or the frontier : one is the parametric (stochastic) approach represented by the Hedonic pricing model and the other non-parametric non-stochastic approach represented by the DEA model [9]. The parametric approach estimates a frontier through the econometrical technique, while the non-parametric approach through the mathematical programming [13].

Unlike Hedonic pricing model, the DEA model does not need to assume a specific distribution in order to estimate the population. In addition, it does not need to set the weighted values of inputs and outputs, since the weighted values of variables are determined when the efficiencies of decision making units (DMUs) are measured by cross-comparing the combinations of inputs and outputs. DEA can also give a manager the substantial help by providing where inefficiency is generated and how inefficiency can be removed.

2.2 DEA Studies on Consumer's Selection

Before consumers select the best among several sellers, they evaluate several sellers in terms of value-for-money. The existing research on the seller evaluation can be classified into linear model, analytical hierarchy process (AHP), principal component analysis

(PCA), game model, activity based costing (ABC), neural network, statistical analysis, and DEA [22]. Among them, DEA method ology is appropriate to evaluate the ratios of value-for-money for the products provided by several online sellers who provide an identical product with the different sale conditions. In cases with similar conditions, many studies, as shown in <Table 1>, use the DEA to evaluate products or sellers to find out a best buy.

Doyle and Green [8] introduce the DEA model to the customer's selection field for the first time. They use DEA model to evaluate many products having similar attributes and provide the information for the choice of goods. Thereafter, many studies [7, 16, 9, 18, 19] use DEA model for the selection of goods or service.

On the other hand, Kleinsorge et al. [10] and Weber [25] applied the DEA model for the supplier (seller) selection in the supply chain network. Several studies, such as Weber and Dasai [26], Weber et al. [27], Talluri [21], Talluri and Narasimhan [22], Zhu [28] and Talluri et al. [23], develop the various DEA models for the seller selection by using Weber [25]'s data set. In Weber [25], the pro-

<Table 1> DEA Studies on Consumer's Selection

Studies	DMUs	Inputs	Outputs
Doyle and Green [8]	Computer printer(n = 37)	Cost	Disc size, CPU speed
Despotis et al. [7] Smirlis et al. [16]	Prepaid cellular phone(n = 42)	Price	Evaluation scores of service provider and the cellular phone.
Fernandez-Castro and Smith [9]	Car(n = 44)	Price	Power, fuel, noise, trunk space, interior.
Staat et al. [18]	Car(n = 30)	price, continued ratio	Resale cost, reliability, safety, the load evaluation, catalyst converter, comfortable
Staat and Hammerschmidt [19]	Car(n = 48)	Price, operating cost	Comfortable, airbag, safety, engine power, the special apparatus, hedonic feature, reputation of a brand
Kleinsorge et al. [10]	Provider's monthly history (n = 18)	Total cost, delivery	Bill, on-time delivery, experience, credit.
Weber [25], Weber, and Dasai [26], Weber et al. [27], Talluri [21], Talluri and Narasimhan [22], Zhu [28], Talluri et al. [23]	Providers(n = 6)	Unit cost	On-time delivery, quality of service

duct (service) that a consumer tries to purchase is the delivery service which a seller provides. In this case, since the seller selection itself becomes the goods choice because the service is not homogeneous. The above research comes in case of purchasing heterogeneous goods through off-line. As a result, our research is distinguished from those listed in <Table 1> because we deal with seller selection in an online transaction process between a buyer and several sellers offering homogeneous goods.

3. FDH Model Measuring Value-for-Money

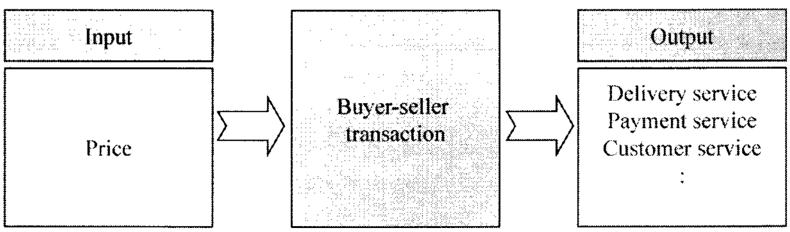
3.1 Value-for-Money

A consumer pays a price then obtains a product and payment service, delivery service, and customer service from a seller. The price which a consumer pays becomes an input. The product and services which a seller provides become outputs. The value-for-money can be measured by the ratio of the outputs which a seller provides by their product and services to the price as an input which a consumer pays for the product and services. When a standardized product such as electronic products is purchased, since the quality of the product which the seller provides is stable and the same, the value getting from it is fixed. In this case, the sale price, seller's characteristics, and services come to determine the selection of a seller by a consumer. Therefore, in case of purchasing standardized products, a buyer-seller transaction process can be shown like <Figure 1>.

While a general production process consists of several inputs and outputs, a buyer-seller transaction process consists of out input and several outputs. Following the studies [7, 9, 16] listed at <Table 1>, we also use price as one input variable to estimate the efficiency, which is considered as value-for-money in our paper.

3.2 The FDH Models for a Seller Recommendation

Fernandez-Castro and Smith [9] estimate



⟨Figure 1⟩ A Buyer-Seller Transaction Process the purchase value frontier of Lancaster comparing CCR, BCC, and the FDH models. BCC model relieves CRS (constant return to scale) of CCR model assumption and allows the VRS (variable return to scale). However, BCC model also has a problem because it deals with arbitrary virtual combinations of inputs and outputs like CCR model. For this reason, Fernandez-Castro and Smith [9] consider FDH model as the most preferable model in the choice problem of a consumer. That means that the efficiency in FDH model was measured based on an actual observed input and output excluding the combination of the virtual input and output. Lee et al. [12] also show that the assumption of the FDH model is the most desirable model in order to measure the purchase value for the customer's selection. In this view of point, we suggest FDH model for the seller selection of a consumer.

FDH model, one of mixed integer programming methods, is introduced by Deprins et al. [6] then developed by Tulkens [24]. It deals with the production provability set consisting of the actually observed input and output variables. FDH model maintains the assumption of BCC model about free disposability about input and output while reliving the assumption of BCC model about convexity. As a result, FDH model is more realistic for measuring a value-for-money rather than CCR or BCC model. <Table 2> shows notations to be used in our FDH model.

Efficient frontier can be divided into the input-oriented and output-oriented. In the input orientation model, we can increase value-for-money score if we reduce an input to the optimal level, given output level. On the other hand, in the output-orientation model, we can increase value-for-money score if we increase an output to the optimal level, given input level. <Table 3> shows the DEA models and improvement policy according to the efficient frontier.

In <Table 3>, since efficiency score θ^* (≤ 1) of input oriented model and efficiency score $\phi^*(\geq 1)$ of output-oriented model are reciprocal $\theta^* = (1/\phi^*)$, the ranks of both models are identical [4]. The Input-oriented model is desirable for the price management, and

〈Table 2〉 Notations in FDH Models

Symbol	Explanation
p_j	the price of jth seller$(j=1,\cdots,n)$
p_o	the price of seller o under evaluation$(o\in\{j\,\|\,j=1,\cdots,n\})$
y_{ij}	the level of i th service of j th seller$(i=1,\cdots,m)$
y_{io}	the level of i th service of seller o under evaluation
λ	the weight of price and the level of service
θ	Efficiency score, i.e. value-for-money

〈Table 3〉 DEA Models and Improvement Policy According to the Efficient Frontier

	Input-oriented model	Output-oriented model
CCR	$\min\theta$ $\sum_{j=1}^{n}\lambda_j p_j \le \theta p_o$ $\sum_{j=1}^{n}\lambda_j y_{ij} \ge y_{io},\quad i=1,\ 2,\cdots,m$ $\lambda_j \ge 0,\quad j=1,\ 2,\cdots,n$	$\max\phi$ $\sum_{j=1}^{n}\lambda_j p_j \le p_o$ $\sum_{j=1}^{n}\lambda_j y_{ij} > \phi y_{io},\quad i=1,\ 2,\cdots,m$ $\lambda_j \ge 0,\ j=1,\ 2,\cdots,n$
BCC	Adding $\sum_{j=1}^{n}\lambda_j=1$ in CCR model	Adding $\sum_{j=1}^{n}\lambda_j=1$ in CCR model
FDH	Adding $\lambda_j\in\{0,1\}$ in BCC model	Adding $\lambda_j\in\{0,\ 1\}$ in BCC model
Improvement policy	$\hat{p}_o=\theta^* p_o=\sum_{j=1}^{n}\lambda_j p_j$	$\hat{y}_{io}-\phi^* y_{io}-\sum_{j=1}^{n}\lambda_j y_{ij}$

output-oriented model is desirable for the service management of a seller.

4. Validation of FDH model with a Data Set of Customers' Choice

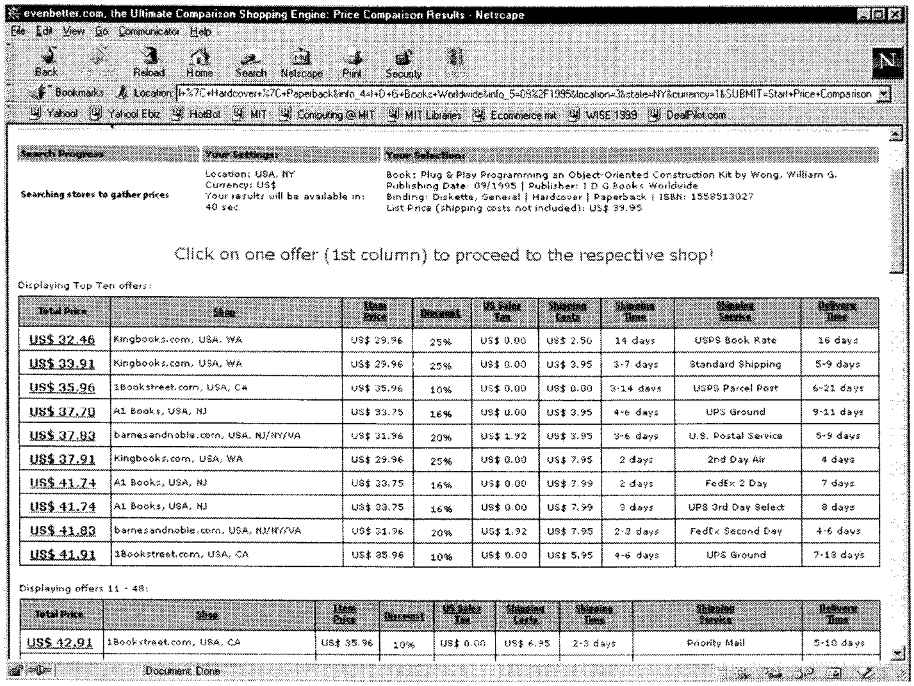
4.1 Dataset

We verify our FDH model by using a shop-bot dataset used by Smith and Brynjolfsson [17]. For 69 days, from August 25 to November 1, 1999, data is collected from Deal Time which is the online comparative shopping service provider. We analyze 100 sessions comprising of 3,707 books, then compare our recommended results with the results of consumer choice behaviors. <Figure 2> shows the screen of the DealTime used for our validity test.

4.2 Variables

To verify our FDH model, we use total price and scores of delivery and brand as one input and two output variables, respectively. One input variable, the total price, includes the price of goods, weighted stage tax, and the shipping charge. Two output variables, the scores of delivery and brand, are transformed from the delivery period and brand used in Smith and Brynjolfsson [17]. The delivery score represents how much customer can be satisfied with the speed of delivery, and the brand score represents the expectation on how much customer can experience easy and-safety payment and on-time delivery.

The delivery period in Smith and Brynjolfsson [17] is the addition of shipping period and the acquisition period of the DealTime. The acquisition period is not the period which a consumer can select as the hanging period when



〈Figure 2〉 DealTime

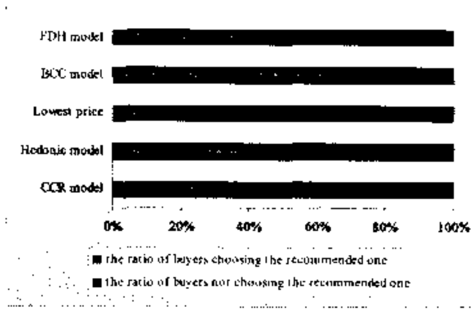
the producer delivers a product to a seller. On the other hand, the shipping period has the option which can receive the fast delivery if a consumer makes payment of the addition shipping charge. Shipping services are divided into three groups such as 'Express shipping' (1~2 days), 'Priority shipping' (3~6 days), and 'Book rate' (over 7 days). Reflecting this classification of shipping period, we give sellers the scores of delivery service as follows : 10 for 1~2 days, 7 for 3~5 days, 4 for 6~15 days, 2 for 15~30 days, and 1 for over 30days.

According to Smith and Brynjolfsson [17], the market share of three big Internet book sellers (Amazon.com, BN.com, and Borders.com) is 88% and all other sellers's market shares are less than 1% each. This means that consumers tend to recognize the brand of a seller as the reliability due to uncertainty of the payment and delivery in the on-line shopping [2]. To consider consumer's value of brand, we give sellers the scores of confidence on sellers as follows : we give Amazon 4, BN 3, Borders 2, and the others 1.

4. 3 Results

<Figure 3> shows the relation between models and consumer's choice behavior. The selection rate in the FDH, VRS, CRS, and hedonic pricing models shows the rate that a

consumer selects the seller whose value-for-money score is 1. The selection rate in the lowest price shows that the rate that a consumer selects the seller offering the lowest price.



〈Figure 3〉 The Selection Result of the Consumer

In <Figure 3>, we can see that only 46% of consumers have selected the seller who presents the least price. This shows that as much as 54% of consumers have considered not only the price but also the characteristics of a seller. This means that 54% of consumers wanted to select sellers with higher value-for-money although they pay more. In the case of the FDH model, 78% of consumers selected the recommended seller according to our model even though the consumers in the data could not see the recommendation by our model. Among them, 32% (78%~46%) of consumers select the recommended one who does not offer the lowest price. This means that most consumers consider not only the price but also delivery and brand name of online shopping sellers. Therefore, this result supports that consumers select the highest value-for-money sellers in their decision making process in purchasing. So, if the decision support by providing the recommendation by value for money can be provided, the consumers' decision making is expected to be improved pretty much

5. An Application of FDH Model

5.1 Comparison Shopping Site for Application

We apply our model to a data set obtained from 'Nawayo.com', a price comparison site of Korea providing the seller evaluation score. There are seven sellers selling a specific notebook with the combinations of price and the levels of payment and delivery services shown in <Table 4>. Both payment and delivery service scores represent the evaluation

〈Table 4〉 Variables for Application

Seller	Inputs	Outputs	
	Price (won)	Payment service score	Delivery service score
1	1,281,000	8	8.54
2	1,282,500	8	8.5
3	1,349,000	8	8.83
4	1,375,000	9	9.29
5	1,443,900	9	8.5
6	1,447,000	9	8.33
7	1,500,000	8	9.43

scores from customers who already bought the product from each seller. Customers gave sellers scores from 1 to 10. The higher score is the better. Payment and delivery service scores refer to how much customers, who bought the products before, are satisfied with payment service and delivery period respectively.

5.2 Recommendation Information for Consumer's Seller Selection

It is not easy for a consumer to select a seller only with price information, due to the uncertainty of characteristics of online shopping related with payment, delivery and so on. So, some comparison shopping services provide the evaluation scores of sellers on payment, delivery and so on. <Table 5> shows price comparison information, seller evaluation information, and seller recommendation information. While the information on price comparison and seller evaluation is provided by current shopbot, the seller recommendation information in the last column of the table is the result from our FDH. Our recommendation information says which seller is the best in terms of value-for-money. Specifically, a seller with 1, the highest value-for-money score, is recommended in our FDH model.

In <Table 5>, seller 1 is the most desirable seller in terms of price while seller 4 is the most desirable one in terms of the evaluation scores of payment and delivery service. The offered prices by seller 1, 2, and 3 are less than seller 4 while the evaluation scores of them are lower than seller 4. Only with price and seller evaluation information, it is not easy to have the assurance about which seller

〈Table 5〉 Price Comparison Information, Seller Evaluation Information, and Seller Recommendation Information

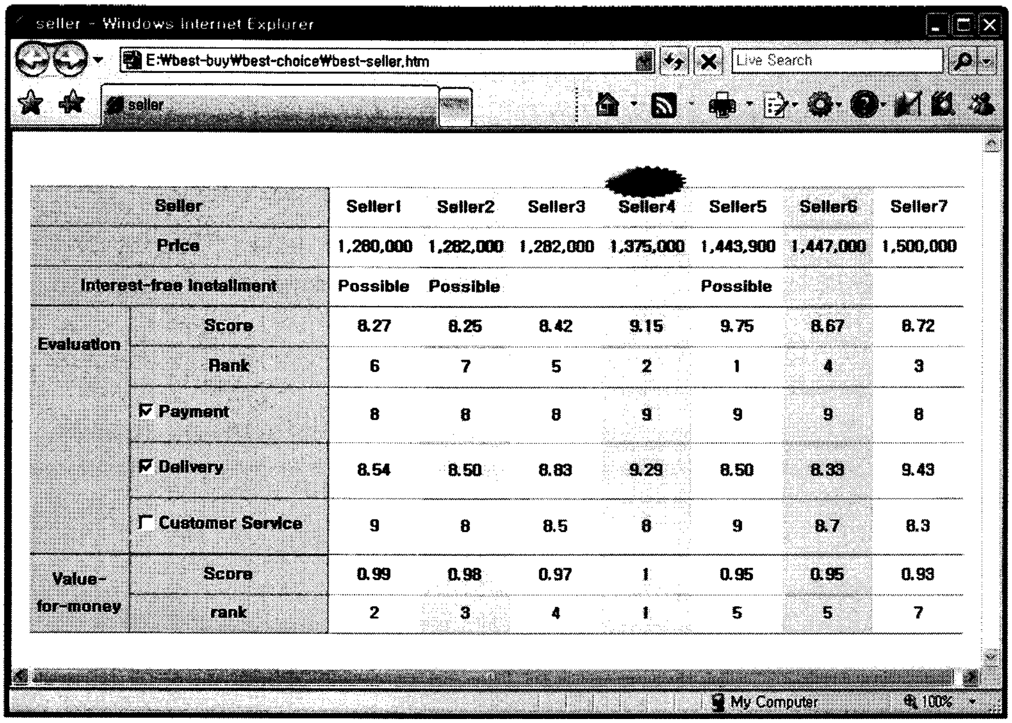
Seller	Price comparison information	Seller evaluation information		Seller recommendation information
	Price (rank)	Payment service score(rank)	Delivery service score(rank)	Value-for-money score (rank)
1	1,281,000(1)	8(4)	8.54(4)	0.99(2)
2	1,282,500(2)	8(4)	8.50(5)	0.98(3)
3	1,349,000(3)	8(4)	8.83(3)	0.97(4)
4	1,375,000(4)	9(1)	9.29(2)	1(1)
5	1,443,900(5)	9(1)	8.50(5)	0.95(5)
6	1,447,000(6)	9(1)	8.33(7)	0.95(5)
7	1,500,000(7)	8(4)	9.43(1)	0.93(7)

is the best. Therefore, the recommendation information that the seller 4 is most desirable in terms of value-for-money will be able to help the seller selection of a consumer. We can implement a seller recommendation system as shown in <Figure 4>. In our recommendation system, a customer can choose the variables to compare the sellers. <Figure 4> shows the case of a customer desiring to compare sellers in the side of the payment and delivery services for price. In this case, a customer checks the payment and delivery services, then our recommendation system calculates the value-for-money using one input (price) and two outputs (payment and delivery scores). As a result, a mark called a "best-buy" is attached to the seller 4 with the highest value-for-money.

An implemented system will help a consumer make a purchasing decision through 'one-click.'

5.3 Benchmarking Information for Seller's Price and Service Management

If a seller drops the price as the rate of the value-for-money score, its value-for-money score can become 1. Therefore, the optimum price level, which is the result of the in-

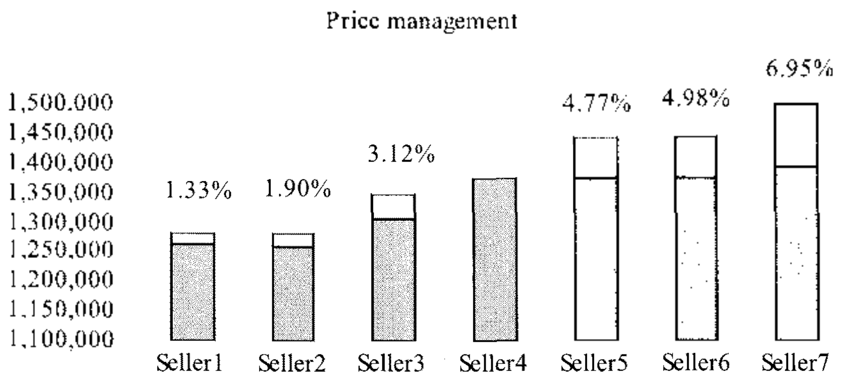


Seller		Seller1	Seller2	Seller3	Seller4	Seller5	Seller6	Seller7
Price		1,280,000	1,282,000	1,282,000	1,375,000	1,443,900	1,447,000	1,500,000
Interest-free Installment		Possible	Possible			Possible		
Evaluation	Score	8.27	8.25	8.42	9.15	9.75	8.67	8.72
	Rank	6	7	5	2	1	4	3
	☑ Payment	8	8	8	9	9	9	8
	☑ Delivery	8.54	8.50	8.83	9.29	8.50	8.33	9.43
	☐ Customer Service	9	8	8.5	8	9	8.7	8.3
Value-for-money	Score	0.99	0.98	0.97	1	0.95	0.95	0.93
	rank	2	3	4	1	5	5	7

〈Figure 4〉 Example of Recommendation System Based on Value-for-Money put-oriented model, can be utilized as the benchmarking information for the price policy shown as <Figure 5>. In order to have the competitive power as seller 4, the seller ranked as the first one, the rest of sellers should lower the price till the optimum level. For example, seller 1 should lower a price as much as 1.33% to become as competitive as seller 4.

Similarly, if a seller raises the service level as much as the rate of the purchase value score, its value-for-money score becomes 1. Therefore, the optimum service level, that is the result of the output-oriented model, can be used as the benchmarking level for the service management policy of a seller as shown in <Figure 6>. In order to have the competitive power as seller 4, the rest sellers should improve the payment or delivery service level till the optimum level. For example, seller 1 should increase a payment or delivery service score as much as 4.81% or 1.35% respectively to become as competitive as seller 4.

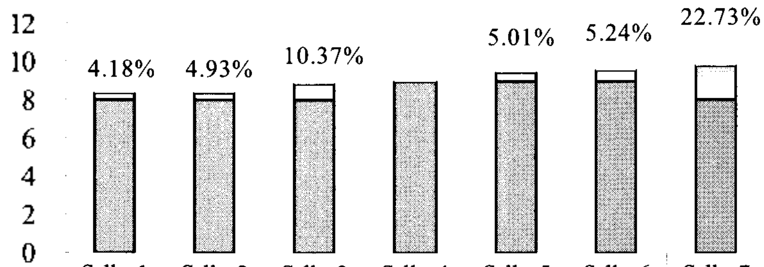
In this way, the optimum price and service levels can be utilized as the benchmarking levels to be reached to increase the competitive powers of sellers whose competitive powers fall behind the leading seller in terms of the competitive power. Furthermore, the price policy in <Figure 5> can be used as the information for a negotiation between consumers and sellers. Service management policy in <Figure 6> also can help a new seller with lower brand recognition to change the service management policy to have the competitive power by improving service rather than lowering a price.



	Seller1	Seller2	Seller3	Seller4	Seller5	Seller6	Seller7
Current price	1,281,00	1,282,50	1,349,00	1,375,00	1,443,90	1,447,00	1,500,00
□ Difference	17,006	24,427	42,084	0	68,900	72,000	104,279
□ Optimal price	1,263,99	1,258,07	1,306,91	1,375,00	1,375,00	1,375,00	1,395,72

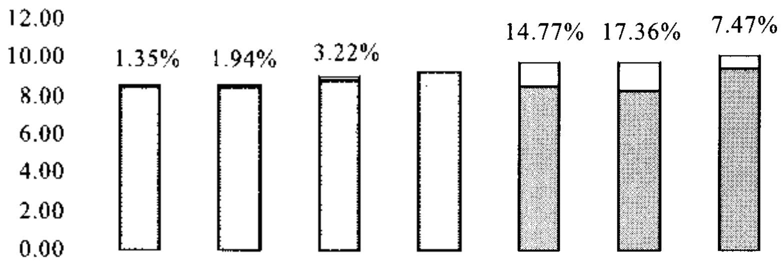
⟨Figure 5⟩ Information for Price Management of Seller

Payment service management



	Seller1	Seller2	Seller3	Seller4	Seller5	Seller6	Seller7
Optimal level	8.385	8.395	8.830	9.000	9.451	9.471	9.818
□ Difference	0.385	0.395	0.830	0.000	0.451	0.471	1.818
□ Current level	8	8	8	9	9	9	8

Delivery service management



	Seller1	Seller2	Seller3	Seller4	Seller5	Seller6	Seller7
Optimal level	8.655	8.665	9.114	9.290	9.756	9.776	10.135
□ Difference	0.115	0.165	0.284	0.000	1.256	1.446	0.705
□ Current level	8.54	8.50	8.83	9.29	8.50	8.33	9.43

〈Figure 6〉 Information for Service Management of Seller

6. Conclusions

Most of former DEA studies have evaluated the performance of production/operation processes for organizations such as banks, school, or public sectors. We suggest that DEA methodology is also good for a buyer-seller transaction process, which can be considered as kind of production process combining inputs and outputs. We present a FDH model appropriate for the frontier estimation methodology for the value-for-money measurement, that is the consumer's selection standard. We also show how to use the FDH model to implement a seller recommendation system.

Most studies on consumer's consumption behavior use a survey or controlled experiment, which do not accurately reflect actual customer's purchase choices. For this reason, we verify our model using a real-world data set collected by shopbots from Deal time, a comparison shopping site. We find that only 46% of the customers selected the seller presenting the lowest price. However, as much as 78% of the consumers selected the seller recommended by our FDH model based on the value-for money. This provides an empirical evidence that most consumers considered not only the price but also the characteristics of sellers such as delivery and brand.

Most DEA studies on consumer's selection deal with the goods choice among heterogeneous ones. A few studies dealt with seller selection are also grouped into studies for goods choice, since their sellers offer heterogeneous goods or service. In contrast, our study is about selecting sellers providing the homogeneous product with different sale conditions, which is one of the most common types of modern market transactions. In addition, this study handles the on line shopping while most studies do off-line shopping. With these differences, it is believed that this study provides exceptional results compared to the other studies on DEA in consumer's purchasing choice even though still the assumptions of DEA in comparing alternatives in its own way remains as the limitation of our method, which does not fully consider all the characteristics of individual utility functions.

We expect that our results help the consumer's decision making for the seller selection in online comparison shopping by recommending the superior among several sellers selling the same product with different price levels and services. Our results also provide sellers the guide line about the service policy and price policy, which is expected to be used as the differentiation strategy of the comparison shopping service providers from many providers and very competitive environment.

These days, some shopbots provide a recommendation information with a customer certified mark or trust store mark. For example, 'BizRate,' 'DealTime,' 'Shopping Smart,' 'Shopzilla,' and 'Epinions,' provide a 'best-buy' mark to help customers to select the best seller. Their best-buy marks are given to the sellers presenting the lowest price among the sellers with the highest evaluations scores. As a result, such recommendation information does not reflect the value-for money. However, online shoppers tend to choose a seller offering the highest value-for money rather than the lowest price. Therefore, in addition to current best buy marks, the recommendation information based on value-for-money can help customers to choose their own best-buy among many sellers offering homogeneous goods and/or services.

If the game theory is applied to the FDH model which we present, it can be used for a negotiation between a buyer and a seller. We will try to reflect the various preferences of a consumer in a recommendations system for further studies. For example, consumers can select the seller selection variables in not only payment service score and delivery service score considered in our study but also a customer service score, interest-free installment, gift, the reserve fund, and so on.

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