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Analysis of the Effect of Second-hand Products' Selling Price in EC Platform by Hedonic Regression

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Abstract

In recent years, the second-hand market in Electronic Commerce (EC) platforms has grown. The trading of second-hand product enables the protect the environment by conserving natural resources, reducing production costs of the equivalent new products, and preventing the second-hand products from becoming waste. On the other hand, it is difficult for second-hand products to determine the selling price. To evaluate the selling price of second-hand products without personal bias, it is necessary to predict prices based on objective information such as specifications and quality of the second-hand product. Hedonic regression is well known to use the prediction for values such as real property and product. This approach is expected to objectively determine prices based on multiple factors, such as specifications and quality, inherent in second-hand products. This study proposes the hedonic regression model for second-hand laptops on the EC platform. First, proposed hedonic regression procedures are illustrated for predicting the selling prices of second-hand laptops. Second, the hedonic regression model is formulated using specification information and quality information. Third, the data processing process is described based on exploratory data analysis. Finally, the proposed regression model is analyzed and discussed.

Keywords
Hedonic Approach, Exploratory Data Analysis (EDA), Ordinary Least Squares Method (OLS), Prediction Model and Morphological Analysis.

1. Introduction
1.1 Background
In recent years, the second-hand market in Electronic Commerce (EC) platforms has grown (Ministry of Economy, Trade and Industry 2021). One of the advantages of the trading in EC platform is that customers can find out the specifications and quality of second-hand products without having to visit a physical store. Additionally, the trading of second-hand products enables to protection of the environment by conserving natural resources, reducing production costs of the equivalent new products, and preventing second-hand products from becoming waste (Yeh et al. 2011). On the other hand, since second-hand products vary, their potential value is not known in advance (Nakajima et al. 2020). Therefore, this makes it difficult to procure second-hand products, predict sales profits, and determine the selling price. To evaluate the selling price of second-hand products without personal bias, it is necessary to predict prices based on objective information such as specifications and quality of the second-hand product. Hedonic regression is a well-known method for predicting the values or the demand of a product (Diewert 2003). It applies multiple regression techniques to large data sets and requires a formal basis in microeconomic theory (Helim 2009). Therefore, the hedonic regression is expected to objectively determine prices based on the multiple factors, such as specifications and quality, which are inherent in second-hand products.

1.2 Purpose of This Study

This study proposes the hedonic regression model with specification information and quality information for the selling price of second-hand laptop on EC platform. First, the proposed hedonic approach procedures are illustrated for predicting the selling prices of the second-hand laptops. Second, the hedonic regression model is formulated using those specifications and quality information. Third, the data processing process is described based on Exploratory Data Analysis (EDA). Finally, the proposed regression model is analyzed and discussed.

This study contributes to creating a determination model that eliminates personal bias and enables appropriate and objective evaluation using second-hand product specifications and quality information in second-hand market on EC platform.

2. Literature Review

Regarding the hedonic regression research, Zanou et al. (2024) analyzed the determination model for the attributes of small ruminants and other specific factors that explain price variations of small ruminants in ordinary period. They improved attributes preferred by buyers through training for breeders on the control of small ruminant reproduction. De Haan et al. (2021) proposed the model-based multilateral price indexes by the time dummy hedonic (TDH) index. They found that their TDH model can reduce the effect of overfitting compared with the time-product dummy index in the case of T-shirt. Rosen (1974) sketched a model of product differentiation based on the hedonic hypothesis. The products in that model are valued for their utility-bearing attributes or characteristics. The proposed model drew out the observational consequences of the construct of implicit markets for characteristics embodied in differentiated products. Bajari et al. (2011) approached the hedonic pricing relied on an assumption about home buyer rationality. They the suggest that ignoring bias from time-varying correlated unobservable considerably understates the benefits of a pollution reduction policy.

With respect to pricing on EC platform, Kuwata et al. (2021) estimated the maximum listing price using random forest, which uses multiple decision trees based on sales history data of secondhand fashion items. Chea and Sheldon (2016) studied the dynamic pricing of tasks online the “gig” and “sharing” economy platforms influence the supply of labor on the intensive margin. They observed that dynamic pricing significantly increases the efficiency of on-demand service markets. For example, the dynamic pricing indicated that jobs are widely distributed across workers and in prevailing market conditions can fluctuate across both time and location on the EC platform. Kumar et al. (2023) developed a novel deep learning algorithm, namely Weight-Optimized Long Short-Term Memory (WOLSTM) for dynamic pricing in EC platforms based on customer buying behavior. To predict the dynamic pricing of the products on EC platforms, they grouped the similar customers by the k-means approach and applied WOLSTM algorithm. The results of their model, it was indicated that WOLSTM algorithm outperformed state-of-the-art methods regarding the classification metrics and the proposed one yields. Boukhatmi et al. (2023) applied the Design Science Research to build and evaluate an artefact for a photovoltaic digital platform. Their study represented the outcomes of an assessment schema designed to gather information relevant to creating a digital produc passport and a photovoltaic reuse online market place designed to march the supply and demand for second life panels.

3. Methods

3.1 Model of Hedonic Approach

Figure 1 illustrates the hedonic approach procedures for determining selling price of the second-hand laptops. First, data on the specifications and quality of the second-hand laptops are summarized from the EC platform. Next, the price effects of specifications and the quality is clarified through the EDA process. The variable x_i represents the selling price effect of laptop i based on its specification. Additionally, the variable y_i represents the selling price effect of laptop i based on its quality. Finally, hedonic regression is conducted to predict the selling price SP_i of the second-hand laptop i using the specification information x_i and quality information y_i.

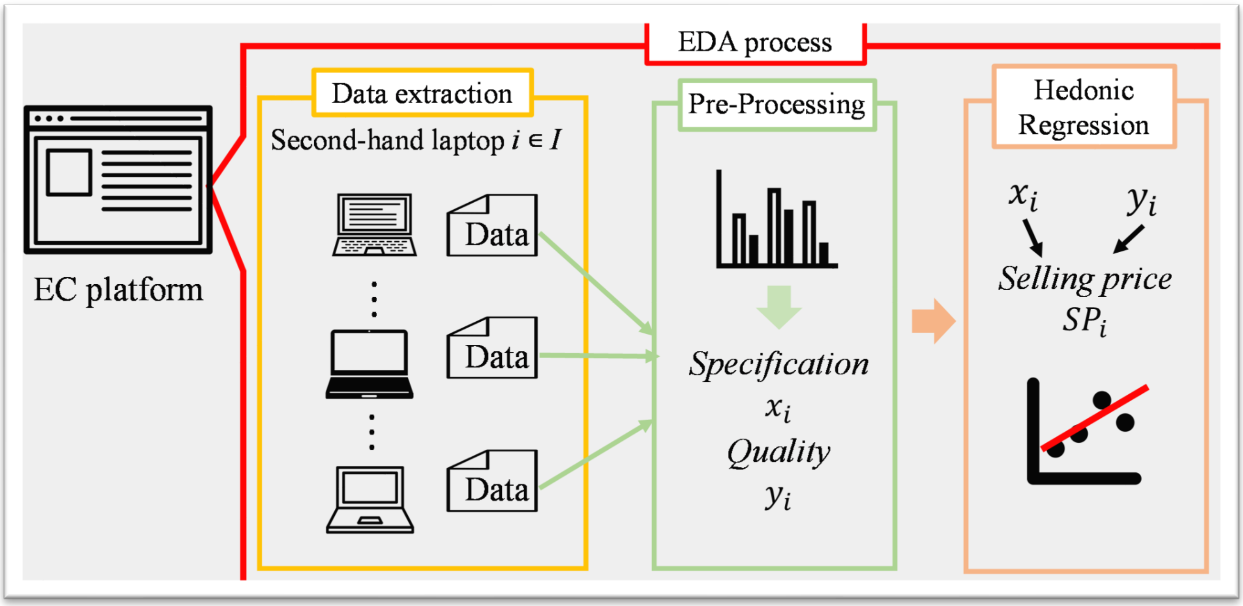

Figure 1. Hedonic approach procedures for selling price of the second-hand laptops

3.2 Notation for Hedonic Regression

To formulate the prediction model for the second-hand laptop i by hedonic regression, notations of specification information x_i and quality information y_i are described as below.

i) Sets

X	:	Set of specification for laptop
Y	:	Set of quality for laptop
A	:	Set of OS types $A \subset X$
B	:	Set of CPU types $B \subset X$
C	:	Set of Memory types $C \subset X$
D	:	Set of SSD types $D \subset X$
E	:	Set of HDD types $E \subset X$
F	:	Set of Ranks $F \subset Y$
G	:	Set of Conditions $G \subset Y$
I	:	Set of second-hand laptops

ii) Indices

x	:	Indices of specification for $x \in X$
y	:	Indices of quality for $y \in Y$
a	:	Indices of OS types $a \in A$
b	:	Indices of CPU types $b \in B$
c	:	Indices of Memory types $c \in C$
d	:	Indices of SSD types $d \in D$
e	:	Indices of HDD types $e \in E$
f	:	Indices of Ranks $f \in F$
g	:	Indices of Conditions $g \in G$
i	:	Indices of a second-hand laptop $i \in I$

iii) Parameters

α_x	:	The selling price effect of the specification x
α_y	:	The selling price effect of the quality y
α_{ia}^{OS}	:	The selling price effect of the second-hand laptop i with OS a
α_{ib}^{CPU}	:	The selling price effect price of the second-hand laptop i with CPU b
$\alpha_{ic}^{\text{MEMORY}}$	:	The selling price effect price of the second-hand laptop i with Memory c
α_{id}^{SSD}	:	The selling price effect of the second-hand laptop i with SSD d
α_{ie}^{HDD}	:	The selling price effect of the second-hand laptop i with HDD e

$\alpha_i^{\text{OPTICAL\_DRIVE}}$: The selling price effect of the second-hand laptop *i* with or without Optical Drive
$\alpha_{if}^{\text{RANK}}$: The selling price effect of the second-hand laptop *i* with Rank *f*
$\alpha_{ig}^{\text{CONDITION}}$: The selling price effect of the second-hand laptop *i* with Condition *g*

iv) Variables

x_{ia}^{OS} : Binary value, 1 if the second-hand laptop *i* with OS *a*, otherwise 0
x_{ib}^{CPU} : Binary value, 1 if the second-hand laptop *i* with CPU *b*, otherwise 0
x_{ic}^{MEMORY} : Binary value, 1 if the second-hand laptop *i* with Memory *c*, otherwise 0
x_{id}^{SSD} : Binary value, 1 if the second-hand laptop *i* with SSD *d*, otherwise 0
x_{ie}^{HDD} : Binary value, 1 if the second-hand laptop *i* with HDD *e*, otherwise 0
$x_i^{\text{OPTICAL\_DRIVE}}$: Binary value, 1 if the second-hand laptop *i* with Optical Drive, otherwise 0
y_{if}^{RANK} : Binary value, 1 if the second-hand laptop *i* with Rank *f*, otherwise 0
$y_{ig}^{\text{CONDITION}}$: Binary value, 1 if the second-hand laptop *i* with Condition *g*, otherwise 0

v) Evaluation

SP_i : The regression selling price of the second-hand laptop *i*
PX_i : The total price effect of specifications information for the second-hand laptop *i*
PY_i : The total price effect of quality information for the second-hand laptop *i*
$AEP^{\text{SPECIFICATION}}$: The average effect of specifications for the total price
AEP^{STATUS} : The average effect of quality for the total price

3.3 Formulation by Hedonic Regression

Hedonic regression is a hedonic approach method for predicting the values of second-hand product or the demand of second-hand product (Diewert 2003). Hedonic regression has been second-hand in real estate and housing market research (Diewert 2003). The regression selling price of the second-hand laptop *i*, SP_i is formulated by two types of information. Therefore, the hedonic regression is modeled by Ordinary Least Squares Method (OLS) (Baum 2006). Equation (1) represents the regression selling price of the second-hand laptop *i*, SP_i. That is the sum of the total the total price effect of specification information for the second-hand laptop *i*, PX_i and the total price effect of quality information for the second-hand laptop *i*, PY_i.

$$P_i = PX_i + PY_i \tag{1}$$

The selling total price effect of specification information for the second-hand laptop *i*, PX_i is included some selling price effects such as OS α_{ia}^{OS} $(a \in A)$, CPU α_{ib}^{CPU} $(b \in B)$, Memory $\alpha_{ic}^{\text{MEMORY}}$ $(c \in C)$, SSD α_{id}^{SSD} $(d \in D)$, HDD α_{ie}^{HDD} $(e \in E)$, and Optical Drive $\alpha_i^{\text{OPTICAL\_DRIVE}}$ as shown in Equation (2).

$$\begin{aligned} PX_i = {} & \sum_a^{a\in A} \alpha_{ia}^{\text{OS}} x_{ia}^{\text{OS}} + \sum_b^{b\in B} \alpha_{ib}^{\text{CPU}} x_{ib}^{\text{CPU}} + \sum_c^{c\in C} \alpha_{ic}^{\text{MEMORY}} x_{ic}^{\text{MEMORY}} \\ & + \sum_d^{d\in D} \alpha_{id}^{\text{SSD}} x_{id}^{\text{SSD}} + \sum_e^{e\in E} \alpha_{ie}^{\text{HDD}} x_{ie}^{\text{HDD}} + \alpha_i^{\text{OPTICAL\_DRIVE}} x_i^{\text{OPTICAL\_DRIVE}} \end{aligned} \tag{2}$$

Equation (3) shows the total price effect of quality information for the second-hand laptop *i*, PY_i which is the sum of product Rank $\alpha_{if}^{\text{RANK}}$ $(f \in F)$ and Condition $\alpha_{ig}^{\text{CONDITION}}$ $(g \in G)$.

$$PY_i = \sum_f^{f\in F} \alpha_{if}^{\text{RANK}} y_{if}^{\text{RANK}} + \sum_g^{g\in G} \alpha_{ig}^{\text{CONDITION}} y_{ig}^{\text{CONDITION}} \tag{3}$$

3.4 Exploratory Data Analysis (EDA)

EDA is a type of approach to clarify the general structure and obtain descriptive summarize (Chartfield 1986). EDA is enables us to get ideas for a more sophisticated analysis (Chartfield 1986). Based on EDA approach, this study applied to 2 steps as shown in Figure 3.

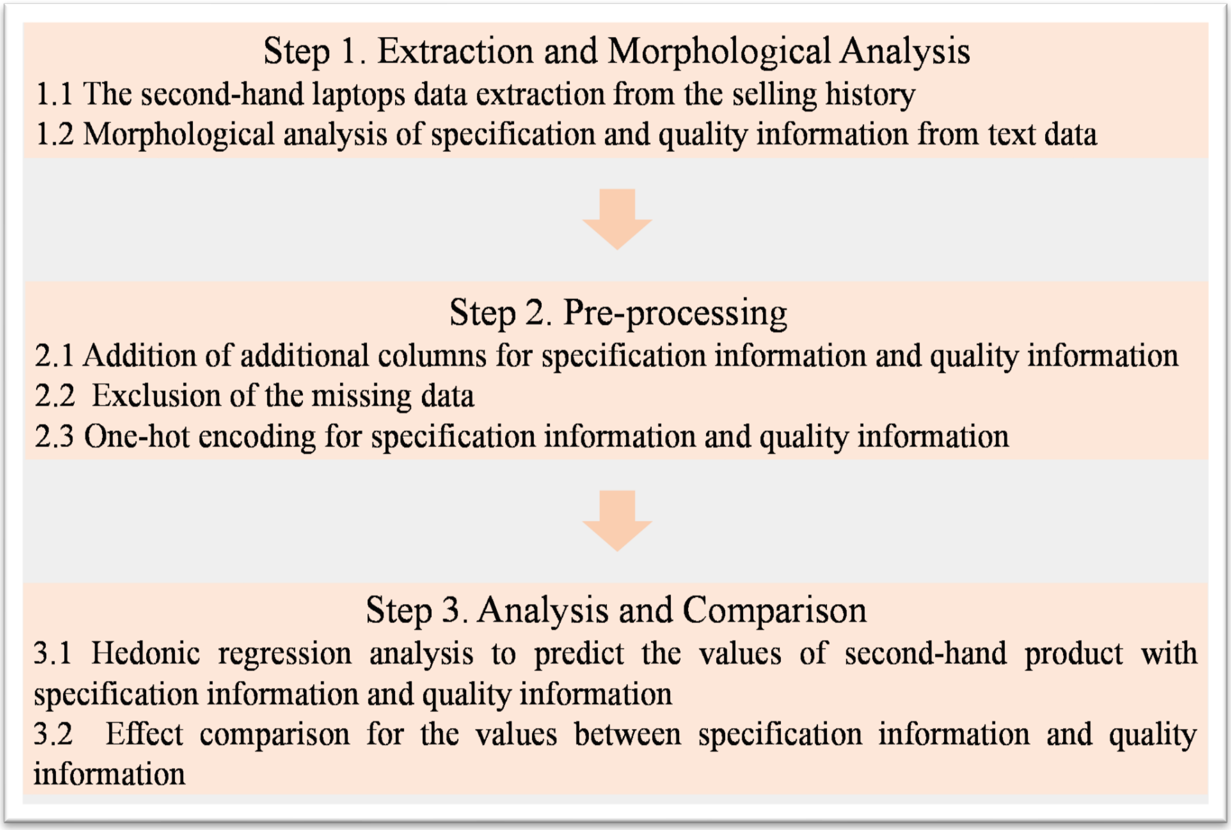

Figure 2. Steps of EDA for the selling history data of the second-hand laptops

- Step 1. Extraction and Morphological Analysis
  In order to analyze the effects of specification information x_i and the quality information y_i on each the selling profits of second-hand laptop i, this study utilizes the sales history data from EC platforms. However, EC platforms typically do not customize their displays to show the specification data and quality data of laptops because the display format is standardized across various items such as laptops, foods, and books. Therefore, the specification information x_i and quality information y_i of second-hand laptop i must be extracted from the sales history using morphological analysis.

  Step 1.1 The second-hand laptop data extraction from the selling history
  First, the sales history data on EC platforms include various items such as machines, food, and books. To focus on second-hand laptops, this study filtered the data by "Item_Id" to extract laptop listings. Additionally, the extracted laptop listings include both new and second-hand products. Thus, this step categorizes them based on the presence of the word "old" in the "Product_Name".

  1.2 Morphological analysis of specification and quality information from text data
  Step 1.2 identifies the specification information x_i and quality information y_i of each second-hand laptop i, which has 9 columns, by morphological analysis. The specification data and quality data are included in sentences on several columns, such as "Product_Name" and "Product Explanation". Noun words in these sentences are extracted through morphological analysis. After this analysis, the specification information x_i and quality information y_i are identified, as shown in Table 1.

- Step 2. Pre-processing for second-hand laptop data
  From Step 1, the specification information x_i and the quality information y_i of the laptop i are obtained. In Step 2, additional columns are creates based on this information.
  2.1 Addition of additional columns for specification information and quality information
  The 8 new columns for the specification information such as OS $\alpha_{ia}^{\mathrm{OS}}$ $(a \in A)$, CPU $\alpha_{ib}^{\mathrm{CPU}}$ $(b \in B)$, Memory $\alpha_{ic}^{\mathrm{MEMORY}}$ $(c \in C)$, SSD $\alpha_{id}^{\mathrm{SSD}}$ $(d \in D)$, HDD $\alpha_{ie}^{\mathrm{HDD}}$ $(e \in E)$, and Optical Drive $\alpha_{i}^{\mathrm{OPTICAL\_DRIVE}}$ and the quality information such as product Rank $\alpha_{if}^{\mathrm{RANK}}$ $(f \in F)$ and Condition $\alpha_{ig}^{\mathrm{CONDITION}}$ $(g \in G)$ are added to each row data.
  2.2 Exclusion of the missing data
  As a result of applying steps up to step 2.1, there are rows with missing data. Since the contents of each second-hand laptop i are independent, any rows with even one missing data are excluded.
  2.3 One-hot encoding for specification information and quality information
  To apply the hedonic regression, the specification information x_i and quality information y_i should be converted to quantitative data. One-hot encoding is a method for converting qualitative data into quantitative data as 0 or 1. Therefore, this study converts the specification information x_i and the quality information y_i into quantitative data using one-hot encoding.

- Step 2. Pre-processing for second-hand laptop data

- Table 1. Extraction items of the second-hand laptops

Type	Item	Detail	Examples
Specifications	OS	Installed OS version	Windows 8, 10, …, macOS
Specifications	CPU	The performance of the built-in CPU	Core i7, …, Ryzen 5
Specifications	Memory	The performance of the built-in Memory	4GB, 8GB, 16GB
Specifications	SSD	The performance of the built-in SSD	128GB, 256GB, 512GB
Specifications	HDD	The performance of the built-in HDD	256GB, 512GB, 1000GB
Specifications	Optical drive	Whether or not an optical drive	with, without
Quality	Rank	Product appearance	D, C, B, A, S
Quality	Condition	Product wear and tear	used, good, unused

3.5 Comparison of The Effects for The Total Price between Specification and Status

To evaluate the cost effects of specifications and quality for the total price, the average effect of specifications for the total price $AEP^{\mathrm{SPECIFICATION}}$ and the average effect of quality for the total price AEP^{STATUS} are calculated as shown Equations (4) and (5), respectively.

$$AEP^{\mathrm{SPECIFICATION}} = \frac{\sum_{x}^{x \in X} |\alpha_x|}{|X|} \tag{4}$$

$$AEP^{\mathrm{STATUS}} = \frac{\sum_{y}^{y \in Y} |\alpha_Y|}{|Y|} \tag{5}$$

4. Problem Example

4.1 EC platform and second-hand laptop information

Table 2 represents the information for the EC platform and second-hand laptop in this study. This study researched a general EC platform. On this platform, shops sell not only laptops but also home appliances, food, and household items. Regarding second-hand laptops, the range of selling prices was between 10,800 yen and 276,667 yen. To ensure that the data was representative of the market for second-hand laptops, products priced below 30,000 yen were excluded.

- Table 2. Extraction items of the second-hand laptops

EC platform information	
Number of EC platform	1
Selling place	EC platform
Sell style	Mall
Selling method	Direct to Consumer (D2C)
Payment Method	Online, Bank transfer, Bill
Second-hand laptop information	
Year of laptop model	from 2007 to 2019
Range of selling price	from 10,800 Yen to 276,667 Yen
Number of learning data	1,064

4.2 Frequency Distribution

Figure 3 illustrated the frequency distribution of the selling prices of the second-hand laptops, which range from 30,000 Yen to 270,000. The selling price range of 30,000 Yen to 60,000 Yen was the highest among 6 ranges. Additionally, 80% of the selling prices were lower than 90,000 Yen.

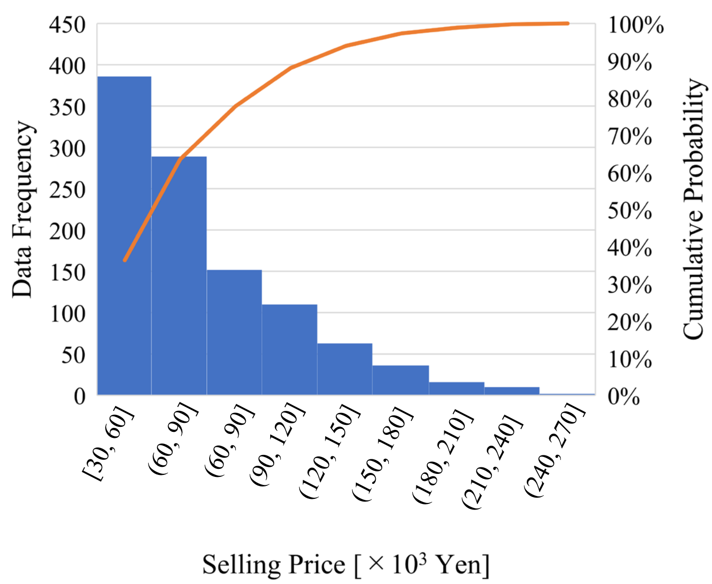

Figure 3. Frequency distribution of the selling price of the second-hand laptops

5. Results and Discussion

5.1 Result of the Selling Price

Figure 4 represented the selling price prediction for the second-hand laptops. From Figure 4, it was found that this regression model with OLS tended to predict to be lower the selling prices of second-hand laptops that actual range from 5,000 Yen to 100,000 Yen. On the other hand, the selling prices of second-hand laptops that were actually over 200,000 Yen were predicted to be higher. One of the reasons was that there were many cases where second-hand laptops with low selling prices were older model. Therefore, this regression model did not consider the price fluctuations over time.

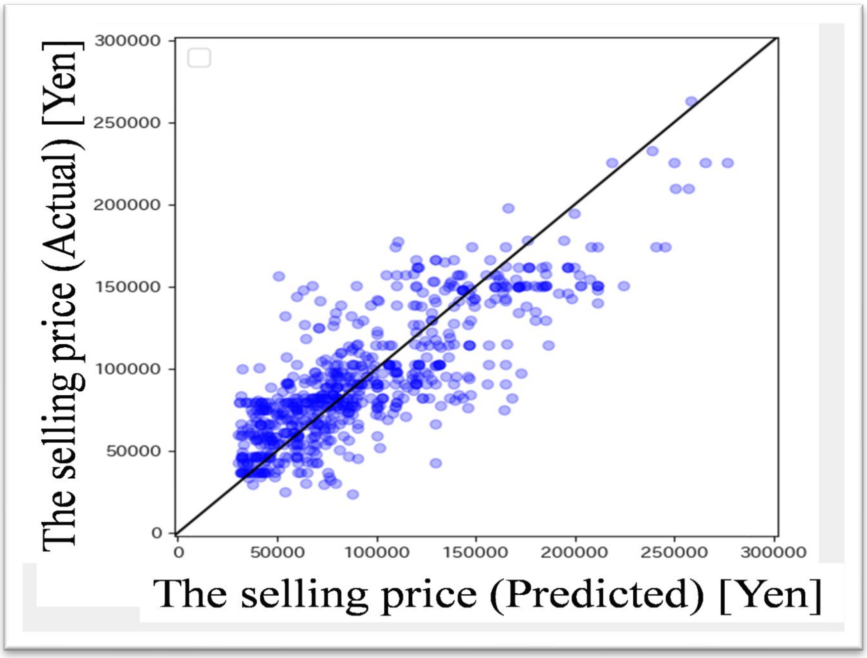

Figure 4. The selling price regression result of the second-hand laptops

5.2 Results of Regression Coefficient and p-values

Figure 5 shows the results of the partial regression coefficients and p-values in this regression model. From Figure 5, the partial regression coefficient of 16 GB memory $\alpha_{ic}^{\text{MEMORY}}(c = \text{"16GB"})$ was the highest among 30 explanatory variables. Compared to 16GB memory $\alpha_{ic}^{\text{MEMORY}}(c = \text{"16GB"})$, the selling price effects of 4GB memory $\alpha_{ic}^{\text{MEMORY}}(c = \text{"4GB"})$ and 8GB memory $\alpha_{ic}^{\text{MEMORY}}(c = \text{"8GB"})$ were decreased. This result indicates that memory specifications $\alpha_{ic}^{\text{MEMORY}}$ significantly affected the values of the second-hand laptops. Additionally, a similar trend was observed for the partial regression coefficient of CPUs α_{ib}^{CPU}. Therefore, it was noted that some specification information, such as memory $\alpha_{ic}^{\text{MEMORY}}$ and CPU α_{ib}^{CPU}, significantly impacted the selling price. Then, both coefficient values of explanation variable related to the optical drive $x_i^{\text{OPTICAL\_DRIVE}}$ showed a positive profit effect on the selling price. It can be considered that some customers prefer the laptops with optical drive ($x_i^{\text{OPTICAL\_DRIVE}} = 1$) to watch DVD drive or use optical drive for work. On the other hand, it can also be considered that some customers prefer the laptops without optical drive ($x_i^{\text{OPTICAL\_DRIVE}} = 0$) because they were lighter. These results show that there was customer demand for laptops with or without optical drives.

On the other hand, the quality information such as condition and rank also had high partial regression coefficient. Especially, the quality of better such as unused condition $y_{ig}^{\text{CONDITION}}(g = \text{"unused"})$ and S rank $y_{if}^{\text{RANK}}(f = \text{"S"})$ presented 48,754 and 25,676 cost effects, respectively.

Regarding p-value of each variable, the proportion of variables with p-values of significance below 5% (p-values of x_i or $y_i \leq 0.05$) is 10 out of 31. From Figure 5, some specification valuables such as Memory $x_{ic}^{\text{Memory}}(c = \text{"4GB"}, \text{"16GB"})$ and with Optical Drive $x_i^{\text{OPTICAL\_DRIVE}}(= 1)$, and some condition valuables such as unused condition

$y_{ig}^{\text{CONDITION}}(g = \text{"unused"})$ and S rank $y_{if}^{\text{RANK}}(f = \text{"S"})$ was showed by 0 p-value. Therefore, it was indicated that both information for specification and quality has the effect for the selling price SP_i.

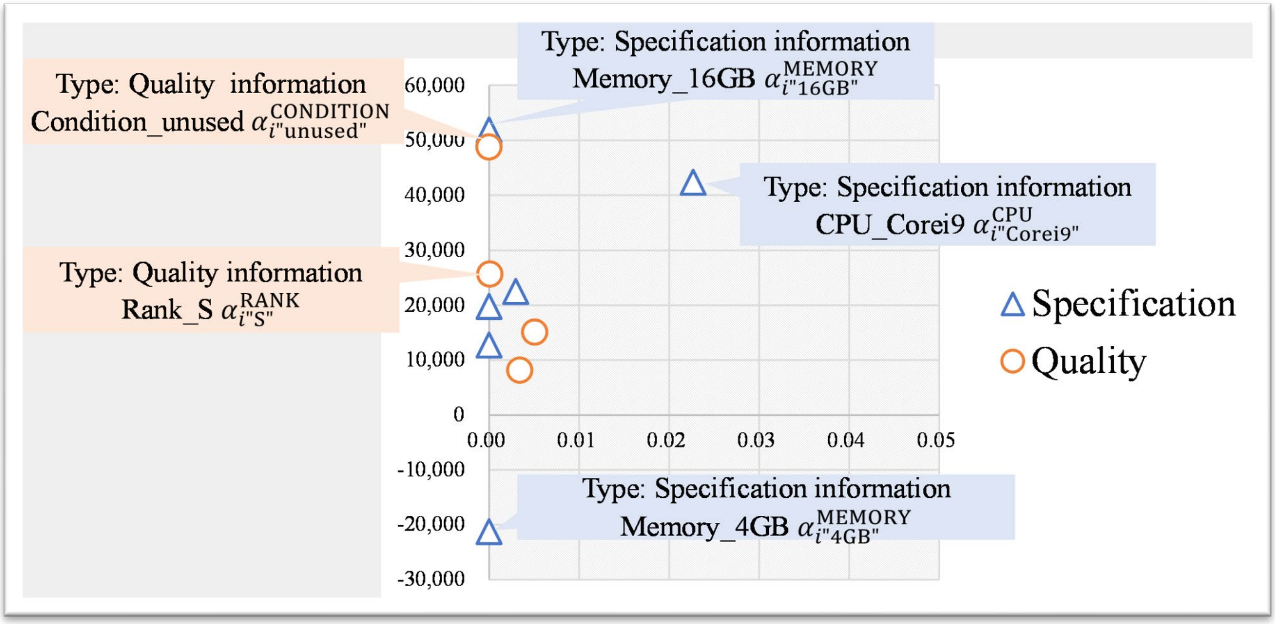

Figure 5. Result of partial regression coefficient and p-value

5.2 Results of p-values

Figure 6 showed the results of the averages for the effect of total price and p-values about the specification and quality information. Compared with the specification information x_i and quality information y_i, the average regression coefficient of the specification information x_i was lower than it of the quality information by 23%. Additionally, p-value of the specification information x_i was also higher than it of the quality information by 73%. Therefore, it can be considered that the selling price of second-hand laptops is determined based on quality information.

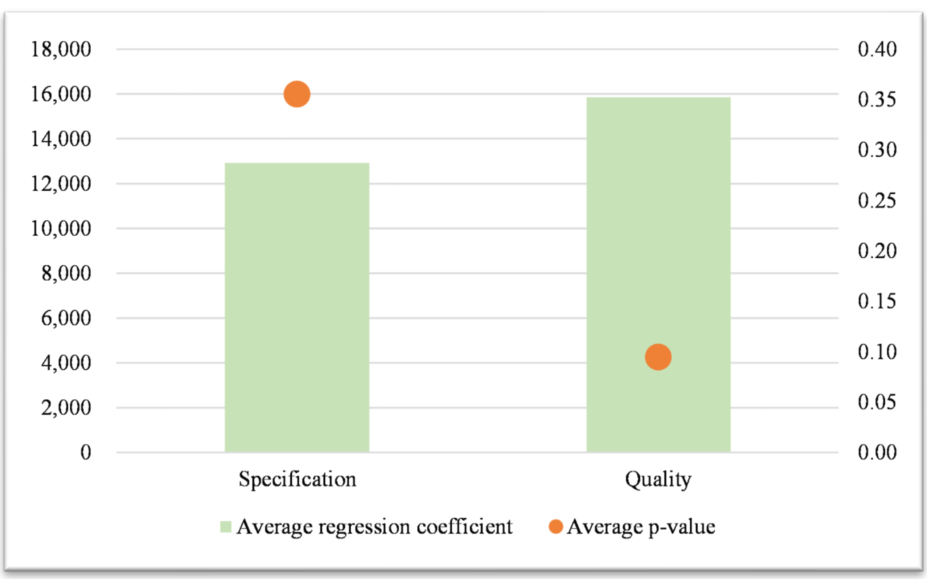

Figure 6. Results of average regression coefficient and p-value for specification information and quality information

6. Conclusion

This study proposes the hedonic regression model for the second-hand product of laptops on EC platform. From results it can be considered that the quality information has more influence than the specification information Future works should design demand model of customer for the second-hand product. Furthermore, it is need to examine the compatibility of the seller's sales price model and the buyer's demand model.

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