Therefore, in this study, to distinguish the above purchase patterns, we extracted consumer characteristics from their pre-purchase behavior and define new variables to represent them. Then, we constructed a consumer purchase prediction model using these variables along with the time variables used in Vieira.

3 Proposal Study

3.1 Newly Created Variables

Before defining new variables indicating consumer characteristics, an overview of the data to be considered in this study is given in Tables 1, 2, and 3. The data acquisition period was from July 1, 2010, to June 28, 2011. In this study, a purchase prediction model was constructed using the conversion (CV) flag as the objective variable. (A classifier that outputs 0 or 1)

Table 1. Access Log Data

Name	*Contents*
Session_ID	session division
Session Starting Time	year, month, day, time
Session Ending Time	year, month, day, time
Session Time	total time of session
Browsing Item Time	total time of browsing item
User_ID	user division
Session PV	page view of session
Genre	item division (0-4)
CV Flag (purchase)	1: purchase, 0: not purchase

Table 2. Orders Data

Name	*Contents*
User_ID	user division
Purchase Amount	purchased item price
Purchase Quantity	purchased item quantity

Table 3. Customer Data

Name	*Contents*
User_ID	user division
Sex	1: male, 0: female
Age	age

The following five variables newly created in this study to show the characteristics of consumers:

(1) item PV

(2) number of sessions

(3) number of product types viewed

(4) site access rate

(5) preference diversity

First, “Item PV” is a variable that indicates the number of times a consumer has viewed a product during a session. By checking this number of times, we can distinguish between the purchasing patterns in Figures 3 and 4. The method of creation is to tally the number of times the consumer accessed the product page during the session.

Next, the “number of sessions” is a variable that indicates the number of times the consumer accessed the session. This variable is divided into four groups: morning, afternoon, evening, and night, and more, weekday or weekend (based on the data collected in this study). The reason for separating weekdays and weekends is to understand whether consumers are accessing the site on weekdays or weekends, or only on weekends.

The third variable, “Number of Product Types Viewed,” indicates the number of product types that the consumer browsed during the session. This variable is also split because of the data used, but the year is split into three parts. It is created by aggregating the number of genre types that users browsed during their sessions.

The fourth, “Site Access Rate," is a variable that indicates the average number of site accesses per month by consumers throughout the year. Therefore, it is created by dividing the number of site accesses per year by 12, and only the value of the last month is excluded to avoid multicollinearity.

The fifth variable, “Preference Diversity,” indicates whether the consumer purchased a product by focusing on only one item or by looking at a variety of products. This variable is the one mentioned in the study by Niimi and Hoshino [10], in which it quantifies the range of item genres being viewed and the degree of dependence on a particular item genre. (e.g., in Table 4, User_1 has equal access to each item genre, while User_2 is biased toward food.)

Table 4. Diversity by Niimi, Hoshino [10]

Item Genre	User_1	User_2
Total Access Count	100	100
Food	33%	90%
T-shirts	33%	5%
Towel	33%	5%
Diversity	?	?

Based on this idea, we created a variable called "preference diversity" in this study. This variable was created because the purchase patterns 3 (Figure 6) and 4 (Figure 7) are possible when using the variable of "Number of Product Types Viewed.” Figure 6 shows the purchase pattern of a person who is strongly considering the purchase of Product A but also considers other products while doing so, and Figure 7 shows the purchase pattern of a person who considers a variety of products (they are indecisive) before purchasing Product A. Consumers with low preference diversity have small uncertainty (large bias) in their browsing behavior and thus resemble the case in Figure 6, while consumers with high preference diversity resemble the case in Figure 7.

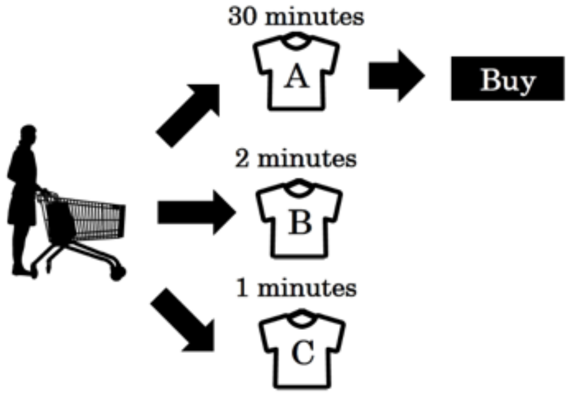

Figure 6. High preference diversity

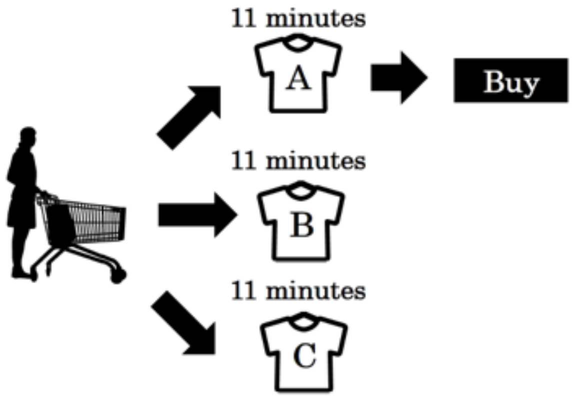

Figure 7. Low preference diversity

This variable is calculated using equation (3), where p is the ratio of viewing time for each genre that the user watched during the session.

$$H = \sum_{i=1}^{m} -p_i log_2 p_i \tag{3}$$

$$\sum_{i=1}^{m} p_i = 1 \tag{4}$$

$$0 \leq p_i \leq 1 \tag{5}$$

3.2 Proposed Model

In this study, a feed-forward neural network (FFNN) with three hidden layers and 10 units per layer was used as the model. The hyperparameters used for the training are listed in Table 5.

Table 5. Hyperparameters of feed-forward neural network

Hyperparameters	
Hod-Out(test size)	0.25
Activation Function	Relu (Hidden Layer), Sigmoid (Output Layer)
Regularization	Bayes Regularization
Gradient Descent	Adam
Learning Rate	1.00E-04
Epoch	20
Batch	30

Bayesian regularization is a regularization method that treats the calculation of weights w by Bayesian posterior probability as synonymous with minimizing the regularized objective function. This method can make learning robust and can retain some advantages in the learning itself, such as optimization of the selection of the validation set, optimization of the size of the validation task, and optimization of the network architecture [22].

$$F = \beta E_D(D|w, M) + \alpha E_w(w|M) \tag{6}$$

where E_D is the average sum of squares of network errors (7), E_w is the average sum of squares of network weights (8), D is the pair of explanatory and objective variables, M is the number of layers, units per layer, and type of activation function, and α and β are regularization parameters.

$$E_D(D|w, M) = \frac{1}{N}\sum_{i=1}^{n}(\hat{t_i} - t_i)^2 \tag{7}$$

$$E_w(w|M) = \frac{1}{n}\sum_{j=1}^{n} w_j^2 \tag{8}$$

The area under the curve (AUC) was used as an evaluation index to compare the accuracy of the model developed in this study to that of Vieira's model. The AUC of interest is the area under the receiver operating characteristic (ROC) curve, where AUC=0.5 indicates a random classifier, and 1 means a perfect classifier. The ROC curve is a graph that shows the relationship between the true positive rate and false positive rate in binary classification. (The vertical axis is the true positive rate, and the horizontal axis is the false positive rate.)

Table 6 shows the differences in the explanatory variables (input data) used in Vieira's model and the proposed model. All input data, except for customer attributes, preference diversity, and site access ratio, were averaged per session. Even if the accuracy of both models is comparable, it can be said that we succeeded in building a useful model in that we were able to incorporate more information into the model than in the previous model.

Table 6. Differences in the explanatory variables used the model (Vieira, Proposed model)

	Vieira	*This Study*
Age	○	○
Sex	○	○
Purchase Amount	○	○
Puchase Quantity	○	○
Session PV	○	○
Session Time	○	○
Item Browsing Time	○	○
Item PV	×	○
Site Access Rate (to divide 1 year)	×	○
Number of Sessions (to divide 24 hour and week day or weekend)	×	○
Number of Product Types Viewed (to divide 1 year)	×	○
Preference Diversity	×	○

Permutation importance (PIMP) [23] was used as a method to determine which of the explanatory variables used in the proposed model had the most influence on the objective variable. PIMP compares the accuracy of a model using sorted features with the accuracy of a model using unsorted features; the greater the difference in accuracy, the greater the impact of the reordered features on the prediction target, which is treated as an indicator of the importance of the variables. In (9), $\widehat{MR_{difference}}(f)$ (model reliance) denotes PIMP [24]. Let the training model be f, the objective variable be y, the feature matrix be X = [X1 X2] (Table 6), and the loss function be L. $X_{1[i,\cdot]}$ denotes the i-th row of X1, and $X_{2[j,\cdot]}$ denotes the j-th row of X2. $\widehat{e_{switch}}(f)$ denotes the expected loss of features of the model during reordering, and $\widehat{e_{orig}}(f)$ denotes the expected loss of the features of the model before reordering.

$$\widehat{MR_{difference}}(f) := In\ sample\ loss\ of\ f\ under\ noise - In\ sample\ loss\ of\ f\ without\ noise$$
$$= \widehat{e_{switch}}(f) - \widehat{e_{orig}}(f) \quad (9)$$

$$\widehat{e_{switch}}(f) := \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j \neq i} L\{f, (y_{[i]}, X_{1[i,\cdot]}, X_{2[i,\cdot]}) \tag{10}$$

$$\widehat{e_{orig}}(f) := \frac{1}{n} \sum_{i=1}^{n} L\{f, (y_{[j]}, X_{1[j,\cdot]}, X_{2[j,\cdot]} \tag{11}$$

4 Results

The AUC of Vieira's model was 0.58, and that of the proposed model was 0.70. Our model can be considered is more effective in comparison (based on average AUC in 1000 training trials). Welch's test was performed on the AUC calculated from Vieira's model and the AUC of the proposed model, and it was significant with a p-value of 0.00 The test conditions were as follows: significance level of 0.05, power of 0.8, effect size of 0.2, two-tailed test, and the number of samples used was n = 393.

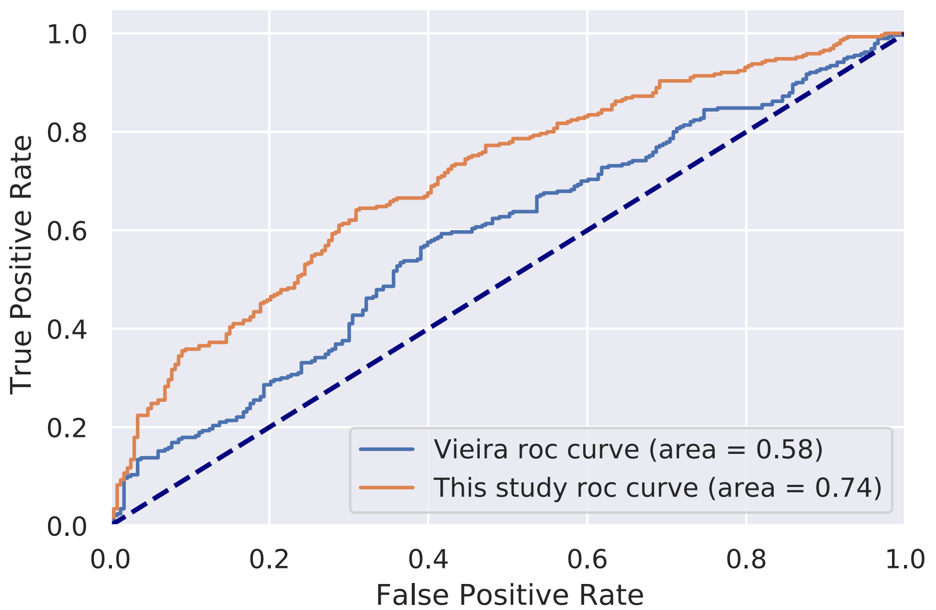

Figure 8. ROC curves for each model

Figure 8 represents AUC=0.5 is the dotted line, AUC=0.58 for Vieira's model is the blue line, and AUC=0.74 for the model in this study is the orange line.

Table 7 shows the PIMP of each feature used in the proposed model. The value of PIMP indicates the extent to which the accuracy of the model decreases when the features are randomly sorted. Therefore, the smaller the value of the PIMP of a feature, the stronger the influence of that variable on the model. Table 7 indicates that the variables “Age,” “Site Access Rate in April,” and “Purchase Quantity” have an impact on the objective variable, the CV flag. On the contrary, variables such as “Number of Product Types Viewed (from June 1 to September 30)" and “Preference Diversity” have less influence on the CV flag.

Table 7. PIMP (ascending order) of the features used in the model of our research

Attribute	*PIMP*
Age	**-0.0048**
Site Access Rate (Apr.)	**-0.0031**
Purchase Quantity	**-0.0013**
Number of Product Types Viewed(10/1 ~ 12/31)	-0.0007
Number of Sessions (evening-weekend)	-0.0005
Item Browsing Time	-0.0002
Session PV	-0.0001
Session Time	0.0003
Site Access Rate (Sept.)	0.0005
Item PV	0.0006
Number of Product Types Viewed(1/1 ~ 5/31)	0.0011
Site Access Rate (March.)	0.0011
Number of Sessions (night-weekend)	0.0013
Number of Sessions (evening-weekday)	0.0015
Number of Sessions (morning-weekend)	0.0018
Number of Sessions (noon-weekday)	0.0021
Site Access Rate (Aug.)	0.0022
Number of Sessions (morning-weekday)	0.0025
Site Access Rate (Feb.)	0.0026
Number of Sessions (noon-weekend)	0.0026
Sex	0.0031
Number of Sessions (night-weekday)	0.0049
Site Access Rate (May.)	0.0061
Site Access Rate (Nov.)	0.0065
Purchase Amount	0.0067
Site Access Rate (Oct.)	0.0068
Site Access Rate (Dec.)	0.0070
Site Access Rate (Jul.)	0.0079
Site Access Rate (Jan.)	0.0099
Number of Product Types Viewed (6/1 ~ 9/30)	**0.0242**
Preference Diversity	**0.0594**

5 Discussion

The results in Table 7 show that “Age,” “Site Access Rate in April,” and “Purchase Quantity” have an impact on consumer purchases. The influence of “Age” and “April Site Access Rate” on consumer purchases can be attributed to the data used in this study (which depends on the target customer and product). It is not surprising that the higher the purchase quantity, the more active the consumer's purchasing activity on the site.

However, the longer consumers spent browsing products, the more likely they were to purchase products from the company operating the site, and we assumed that this factor would have a significant impact on consumer purchases, but the results were surprising. Specifically, the users of the site that was the subject of analysis in this study were mostly older, and seasonality existed in the products of this site. Neither “Session Time,” “Session PV,”, “Item Browsing Time” nor "Item PV" had a significant impact on consumers' purchases. This is because, first of all, the time indicator is a value that is always counted when a consumer makes a purchase. In addition, it is not necessarily a factor that contributes to consumers' 'purchase' because it includes the possibility that consumers are just browsing the Internet without any intention to purchase. “Session PV” and “Item PV” may be because of the fact that consumers were comparing products with other sites and did not purchase on this site because of the product's performance, price, or outside promotions.

From Table 7, it can be observed that “Number of Product Types Viewed (6/1-9/30)" and “Preference Diversity” do not affect consumers' purchases at all, but rather the AUC is increased by randomly sorting the variables. For the former, only the results from June 1 to September 30 show an increase in AUC in the opposite direction, which may be because of the nature of the data collected for this study. However, for the preference diversity, the introduction of consumer behaviors, represented in Figure 6 and 7, decreased the accuracy of the model. One possible reason is that, according to Figure 9, consumers in the data in this study tend to exhibit more of the behaviors shown in Figure 7 (behaviors with low preference diversity). Therefore, it is highly likely that this variable, which separates Figure 6 and 7, is noise in the proposed model.

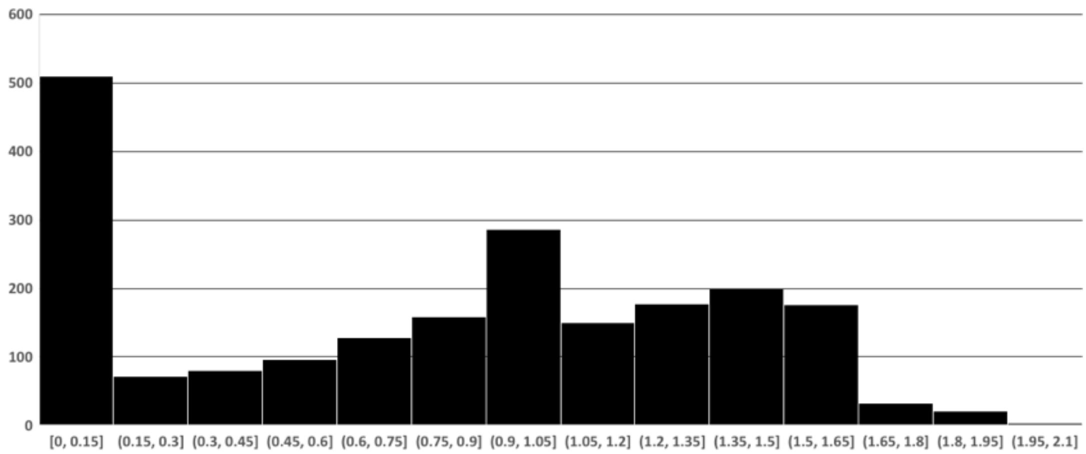

Figure 9. Preference Diversity (histogram)

One example of a marketing strategy based on these results and considerations would be to send thank-you e-mails to consumers who purchased the most in each age group, or to issue coupons to encourage further purchases.

Figure. 9 also shows that the data targeted in this study contains many consumers with low preference diversity, i.e., consumers who can't which ones to buy on the site. Therefore, it is possible to send push notifications on the site to these consumers to relieve their confusion.

In this study, we were not able to ascertain the reasons why consumers did not compare products with other sites and make a purchase. We believe that one approach to avoid losing purchase opportunities is to consider the timing of campaigns that were conducted in other sites.

6 Conclusion and Future Challenges

In this study, we developed a consumer purchasing behavior model that considers consumer characteristics expressed by the time spent on a site and other pre-purchase behaviors. We used Vieira’s [9] findings and created a new model that incorporates consumer characteristics that were not considered in his model, such as newly created explanatory variables based on the research of Niimi and Hoshino [10]. The AUC was used as the evaluation index of the model. As a result, the proposed model has a higher AUC than Vieira's model, indicating that the proposed model is more effective. Next, we confirmed the importance of the features used in the model using permutation importance (PIMP) [23]. The results showed that “Age,” “Site Access Rate (April),” and “Purchase Quantity" influenced consumers’ purchases. On the contrary, “Item Browsing Time,” “Session Time,” “Session PV,” and “Item PV" had little effect on consumer purchases. In addition, “Preference Diversity" separating the purchase patterns in Figures 6 and 7 was found to reduce the accuracy of the model. From these results, it can be concluded that this research has made an academic contribution in that we were able to construct a model that more successfully captures consumer purchasing behavior, and it also has social significance in that we were able to more accurately understand the factors that influence consumer purchasing, allowing us to develop effective marketing strategies.

Owing to data limitations, we were not able to obtain information such as referral data for this survey, so we were unable to confirm consumer migration. By checking this data, we can understand which pages on the site consumers spend the most time on and which pages they view the most. This allows us to consider new marketing strategies, such as inserting ads on pages that are viewed for longer periods of time. In addition, by using affiliate data, when consumers compare products or move to other sites, it is possible to trace their footsteps and confirm the site from which they finally purchase products. This may enable the revelation of the reasons why consumers did not purchase on our site compared to other sites, which we were not able to confirm in this survey. In addition, product reviews and product rating values that exist in mall-type stores such as Amazon did not exist in the e-commerce sites that were the subject of this study. As this data can be a factor in consumer purchasing behavior, it can be captured and incorporated in a future model.

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