International Journal of Service and Knowledge Management
International Institute of Applied Informatics
2022, Vol. 6, No. 1, IJSKM633

A Purchasing Prediction Model Considering Pre-purchase Behaviors

Yuto Fukui [†], Tomoaki Tabata [†], Takaaki Hosoda [*]

Abstract

Consumer purchase behavior models in marketing focus on analyzing the factors that influence consumers' purchases. However, the explanatory variables used in conventional models, such as point-of-sale data from physical stores and customer attributes, do not facilitate the analysis of consumers' purchasing processes, such as the decision making involved in purchases. On an e-commerce site, it is possible to study such purchasing behaviors because data can be collected during the consumer's purchasing process in addition to the data obtained from the result of the consumer's purchase. This study aimed to build a model of consumer purchasing behavior that considers the characteristics of consumers expressed by the time they spend on a website and their behavior prior to purchase and to clarify the importance of the features used in the model so that it can be used in developing effective marketing strategies. This will enable us to build a more sophisticated model of consumer purchasing behavior, which will enable us to understand the factors that influence consumer purchasing behavior more accurately than before, which will enable us to develop precise marketing measures and improve sales for companies.

Keywords: Consumer purchase behavior model, EC-site, Deep Learning, Permutation Importance

1 Introduction

In order to increase the sales of a store or a website, it is necessary not only to increase the number of consumers who visit that sales channel but also to understand what kind of consumers visit and which products are being sold, and to develop a marketing strategy based on the information that can be obtained from this data. However, it is difficult to determine the driving factors influencing consumer purchases from the vast amount of data available.

Therefore, a consumer buying behavior model is necessary. The purpose of this model is to structure consumer purchasing influences; traditionally, discrete choice models such as the

[†] Tokai University, Tokyo, Japan
[*] Advanced Institute for Industrial Technology, Tokyo, Japan

multinomial logit model of McFadden [1] have been widely used because of their affinity with point-of-sale (POS) data.

$$P(x|s,B) = \frac{e^{V(s,x)}}{\sum_{y \in B} e^{V(s,x)}} \tag{1}$$

where s is the individual attributes measured, x represents the products chosen by the consumer, and B is the set of products the consumer can choose from.

The customer's utility function U is divided into a non-stochastic part V and a stochastic part ε of the population as

$$U = V(s,x) + \varepsilon(s,x) \tag{2}$$

This means that the multinomial logit model is a model represented only by the deterministic utility of customer.

Such conventional models focus only on the resulting purchase, and the decision-making process leading to the consumer's purchase is not reflected in the model (Figure 1). For example, even if people of the same age and gender purchase the same product, they are treated in the same way in the model. E-Commerce sites can obtain data not only from purchase results, such as POS and customer attributes but also consumer access logs. This makes it possible to construct consumer purchasing models that consider the consumer decision-making process (Figure 2). Prior studies using data from e-commerce sites have combined measurement-level classifiers such as neural networks based on consumers' purchase patterns on the Web [2], modeled customer interactions on specific websites, identified the factors that contribute to them [3], and developed trust relationships with customers [4]. By analyzing customer behavior on e-commerce sites, we can improve website content and design, customize websites, build stronger relationships with customers, enhance customer communication, and improve customer service [5]. In addition, there have been many studies on predicting customer purchases and analyzing factors using machine learning and neural networks on e-commerce sites [6], [7], [8].

Figure 1: Conventional Data Acquisition (physical store)

Figure 2: Present Data Acquisition (online store)

In this study, we focused on the work by Vieira [9], wherein data from e-commerce sites were used to predict purchases and solve certain problems. He applies modeling techniques such as Logistic Regression, Random Forest, Deep Belief Networks, and Stacked Denoising auto-Encoders to predict customer purchases in sessions. More specifically, in a very sparse data set, he has constructed a consumer purchase prediction model based on the time spent by customers on the site, the time spent on products, etc. He has evaluated the model using AUC, and has shown that boosting methods such as random forests are more accurate than linear models such as logistic regression. It also showed that the accuracy is higher architectures like deep learning are more accurate than those modeling. This will enable us to build a more sophisticated model of consumer purchasing behavior, which will enable us to understand the factors that influence consumer purchasing behavior more accurately than before, which will enable us to develop precise marketing measures and improve sales for companies. For example, this can lead to the development of a system that can recommend appropriate products in a specific session. However, he has not incorporated consumer characteristics into the model. Therefore, we incorporated the consumer characteristics mentioned in the study by Niimi and Hoshino [10] into Vieira's model and construct a new consumer purchase prediction model that incorporates these variables. We then check the extent to which the variables used in the model affect the objective variables and apply the results to marketing strategies.

2 Previous Study

One of the decisions that we humans make every day is to purchase a product or service. Although the decision to buy or not to buy is considered to be mainly based on price, the purchase decision in general is complex and many factors influence the process before the final decision is made [11]. For example, factors such as products introduced by celebrities and product packaging influence consumers' purchases [12]. In online shopping, factors related to the usability of the website, such as website design, download speed, and information search convenience, as well as factors related to the trust in the company providing the website, such as the reputation of the website by others and the brand, affect the purchase [13]. From the above examples, it can be confirmed that a variety of external factors influence consumers' purchasing decisions.

On the other hand, it has been confirmed that internal factors, i.e., psychological aspects and types of consumers, also affect purchasing behavior. For example, consumers who experience emotional experiences such as pleasure and relaxation when purchasing products will have higher purchase intentions [14], and consumers who purchase products impulsively will have their own characteristics such as age, gender, and culture as determinants of their purchases [15]. Thus, there are countless factors that can contribute to a consumer's purchase, and these factors vary depending on the product. For example, if the product that the consumer is purchasing is a luxury brand, the social influence of the product will affect the consumer's purchase intention [16].

Based on the premise that there are a wide variety of consumer purchasing factors, companies analyze the influences that lead to the purchases of the consumers who visit them, and use the results to conduct marketing. Specifically, they use so-called data mining [17] techniques such as mathematics, statistics, machine learning, and artificial intelligence to perform consumer segmentation, behavior prediction, and recommendation. If we focus on consumer behavior prediction, especially purchase prediction, there are three main research fields [18], of which this research focuses on 1. (cited from [18].)

1. *Predict if a current user online session or visit will end up with a purchase or not.*
2. *Predict customers purchase behavior concerning their buying decisions. For instance, to foresee what product or category a customer will buy; to predict the time or period likely to witness a purchase; to predict the next amount customers are likely to spend in their purchases.*
3. *Predict the intention of customer visits online.*

When a consumer visits a store or a website, a purchase prediction model exists to predict whether the visit will eventually lead to a purchase. This model represents the behavior of consumers when they purchase some products, and by using this model, we can not only predict consumers' purchases but also understand their purchase intentions, i.e., analyze the factors that influence their purchase behavior [19].

Here, since e-commerce provides data on the actions taken by consumers before making a purchase, the model can reflect these actions before the consumer makes a purchase decision. In e-commerce, predicting the purchase of a product based on the consumer's behavior in the site and analyzing the intentions of the consumer are important for marketing strategies [20].

The purpose of this study is to build a purchase prediction model using data from an e-commerce site, to understand the purchasing factors of consumers, and to use the results as material for developing marketing strategies. We will build a model that overcomes the limitations of that research.

In the study by Vieira [9], a consumer purchase prediction model (Figure 3) was constructed with product price, mean items price of item purchase, click to purchase ratio, median number of sessions leading to purchase, number of clicks in a session, timeframe when the session occurred, number of page views, words of description about products using 50 dimensions vector composition (excluding stop words), session time, and product browsing time as explanatory variables, and the objective variable was whether the customer had purchased the product (0 or 1).

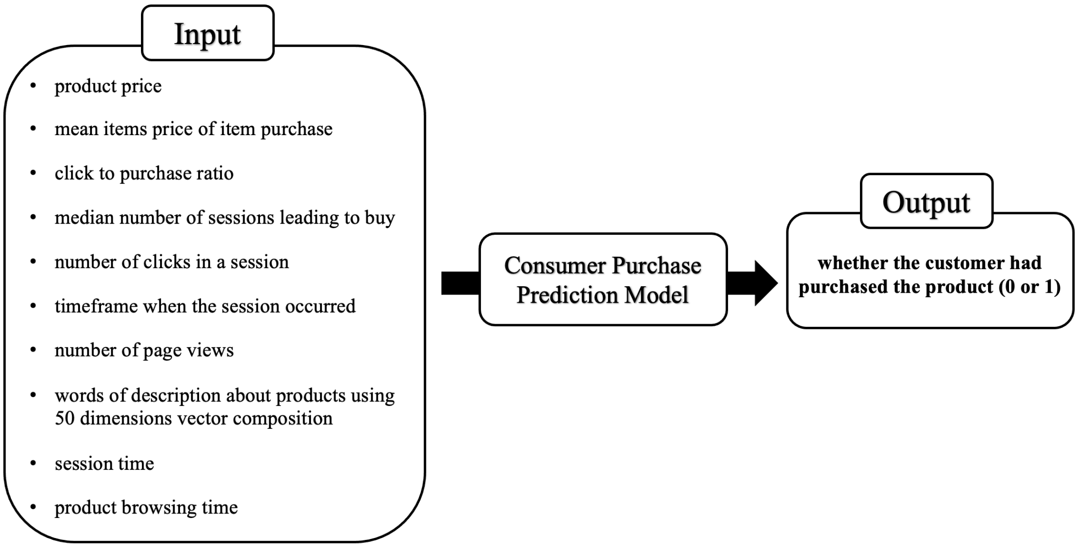

Figure 3. Vieira's Model Structure

This allows us to predict whether a consumer who enters a site (session start) will purchase a product before leaving the site (session end). By incorporating the perspective of time into the explanatory variables, it is possible to ascertain whether the consumer made the purchase after careful consideration or impulsivity. However, this alone is not sufficient to consider the differences between, for example, purchase pattern 1 (Figure 4) and purchase pattern 2 (Figure 5). Figure 3 shows the purchase pattern of a consumer who looked at products A, B, and C in order and finally purchased product A. Figure 4 shows the purchase pattern of a consumer who looked at product A and finally purchased product A. In Vieira's model, if consumers with these buying patterns (Figures 4 and 5) have the same time to purchase, it is impossible to distinguish between them.

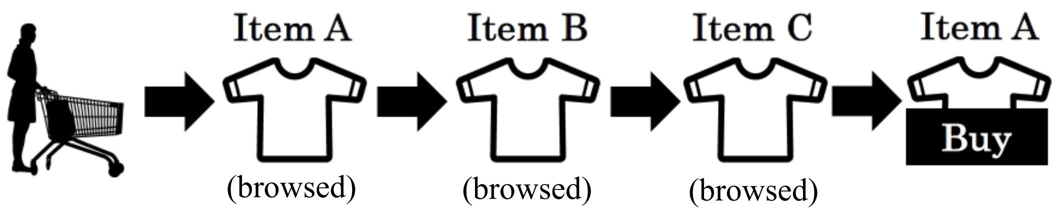

Figure 4. Purchasing Pattern 1

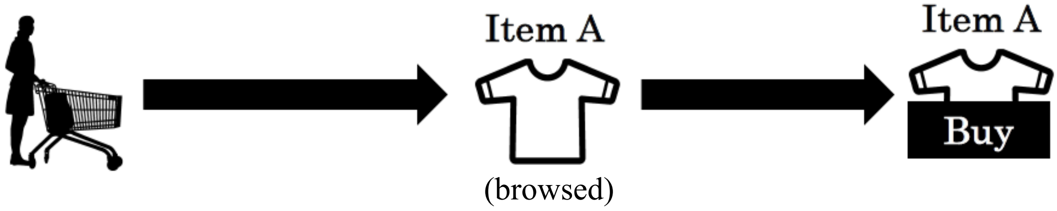

Figure 5. Purchasing Pattern 2

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.

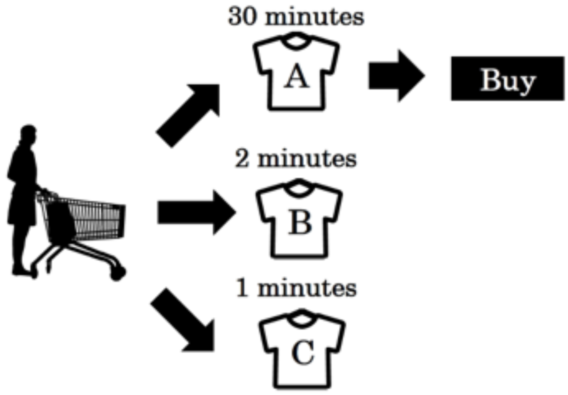

Figure 6. High preference diversity

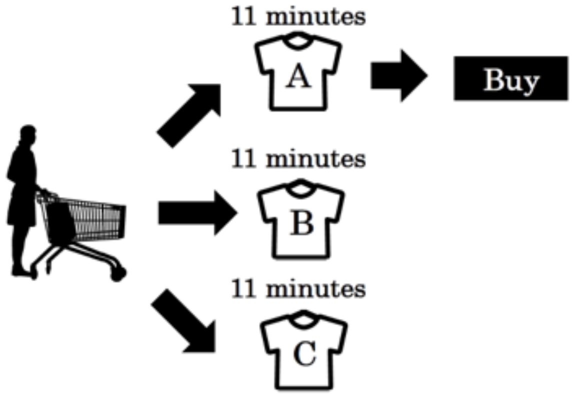

Figure 7. Low preference diversity

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.

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

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

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

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 regulari-zation 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), $MR_{\widehat{difference}}(f)$ (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. $e_{\widehat{switch}}(f)$ 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.

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

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

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

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.

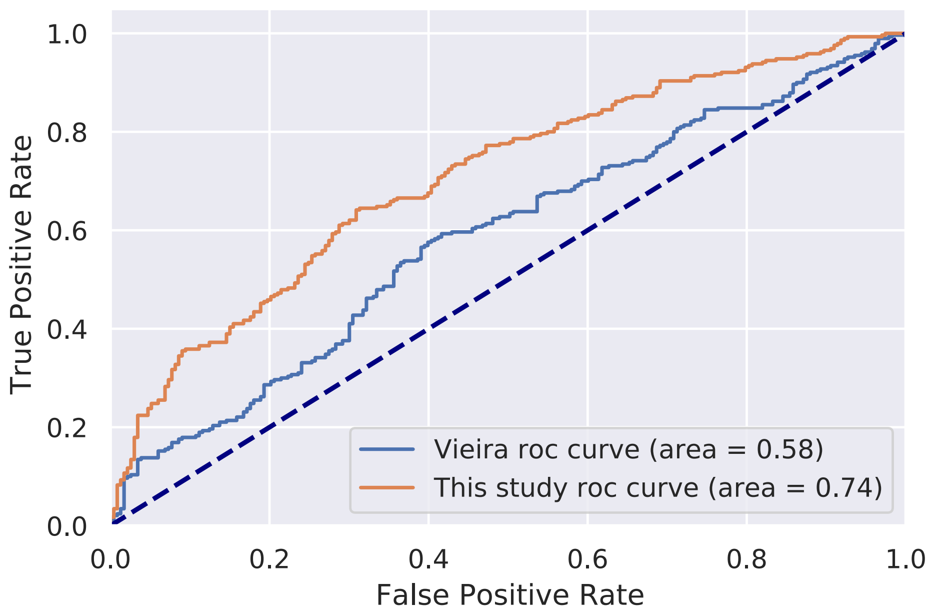

Figure 8. ROC curves for each model

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.

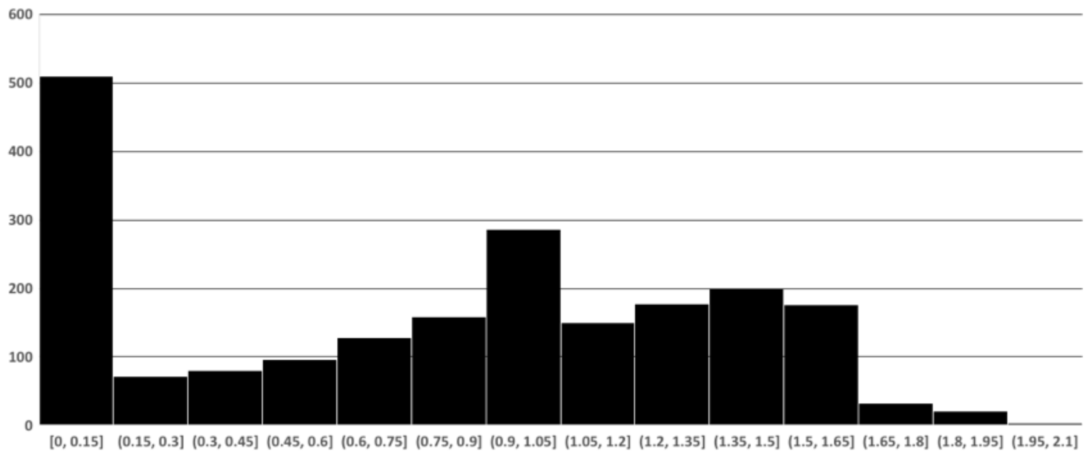

Figure 9. Preference Diversity (histogram)

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.

References

[1] McFadden, D., “Conditional Logit Analysis of Qualitative Choice Behavior,” In P. Zerembka, ed., Frontier in Econometrics, New York: Academic Press 1973

[2] Eunju, K., Yillbyung, L., Wooju, K, “Combination of multiple classifiers for customer’s purchase behavior prediction,” Decision Support Systems, vol. 34, no. 2, pp. 167-175, January 2003

[3] William, K.D., Charles, B, Denise, J.L., “Toward an Integrated Framework for Online Consumer Behavior and Decision Making Process: A Review,” Psychology and Marketing, vol.27, no. 2, pp. 94 - 116, February 2010

[4] Mahmud, A. S., “Online Buying Behavior and Perceived Trustworthiness,” British Journal of Applied Science & Technology, vol. 3, no. 4, pp. 662-683, 2013

[5] Mamata, J., Pratap, K.J. M., Sujoy, G., “A stochastic model of e-customer behavior,” Electronic Commerce Research and Applications, vol. 2, no. 1, pp. 81-94, March 2003

[6] Orogun, A., Bukola, O., “Predicting Consumer Behaviour in Digital Market: A Machine Learning Approach,” International Journal of Innovative Research in Science, Engineering and Technology, vol. 8, Issue 8, August 2019

[7] Laura, M. B (Stroie)., "Predicting Consumer Behavior with Artificial Neural Networks," Procedia Economics and Finance, vol. 15, pp. 238-246, 2014

[8] Zaiyong, T., "Improving Direct Marketing Profitability with Neural Networks," International Journal of Computer Applications (0975 - 8887) Volume 29 No.5, September 2011

[9] Armando, V., "Predicting online user behaviour using deep learning algorithms," The Computing Research Repository (CoRR), arXiv:1511. 06247, 2016

[10] Junichiro, N., Takahiro, Hoshino., "Predicting Purchases with Using the Variety of Customer Behaviors: Analysis of Purchase History and the Browsing History by Deep Learning," The Japanese Society for Artificial Intelligence, vol. 32, no. 2, pp.B-G63_1-9, 2017

[11] Saavi. S, Ognjen. A, "Machine learning based prediction of consumer purchasing decisions: the evidence and its significance," Conference: AAAI Conference on Artificial Intelligence, February 2018

[12] Faiza. R, Anas. Z, Sohail. Y, Identifying the Factors Affecting Customer Purchase Intention Business Global Journal of Management and Business Research, 2015

[13] E. Lai, Zhaocheng. W, "An Empirical Research on Factors Affecting Customer Purchasing Behavior Tendency during Online Shopping," Conference: Software Engineering and Service Science (ICSESS), June 2012

[14] Amir Nasermoadeli, Kwek Choon Ling & Farshad Maghnati, "Evaluating the Impacts of Customer Experience on Purchase Intention," International Journal of Business and Management 8(6) DOI:10.5539/ijbm.v8n6p128, February 2013

[15] Wahida Shahan Tinne, "Impulse Purchasing: A Literature Overview," ASA University Re-view, Vol. 4 No. 2, July–December, 2010

[16] Regina Virvilaitė, Violeta Saladienė, Jūratė Žvinklytė, "The impact of external and internal stimuli on impulsive purchasing," ECONOMICS AND MANAGEMENT: 2011. 16

[17] Kuang-peng Hung, Annie Huiling Chen, Norman Peng, Chris Hackley, Rungpaka Amy Tiwsakul, Chun-lun Chou, "Antecedents of luxury brand purchase intention," Journal of Product & Brand Management, Article publication date: 20 September 2011

[18] William, K.D., Charles, B, Denise, J.L., "Toward an Integrated Framework for Online Consumer Behavior and Decision Making Process: A Review," Psychology and Marketing, vol.27, no. 2, pp. 94 - 116, February 2010

[19] Douglas. C, Markus. H, Dietmar. N, Markus. H and Marija. B, "Customer purchase be-havior prediction in e-commerce: current tasks, applications and methodologies," In: Interna-tional Workshop on New Frontiers in Mining Complex Patterns, September 16, 2019

[20] Xiaotong. D, ”Online purchase behavior prediction and analysis using ensemble learning,” IEEE 5th International Conference on Cloud Computing and Big Data Analytics, Date of Conference: 10-13 April 2020

[21] Curme. C, Preis. T, Stanley. H.E, Moat. H.S, “Quantifying the semantics of search behavior before stock market moves,” Proceedings of the National Academy of Sciences, 111(32), 11600-11605, 2014

[22] Murat, K., “Predictive Abilities of Bayesian Regularization and Levenberg-Marquardt Algorithms in Artificial Neural Networks: A Comparative Empirical Study on Social Data,” Mathematical and Computational Applications, vol. 21, no. 20, pp. 1-11, May 2016

[23] Andre, A., Laura, T., Oliver, S., Thomas L., “Permutation importance: a corrected feature importance measure,” Bioinformatics, vol. 26, issue 10, pp. 1340-1347, April 2010

[24] Aaron, F., Cynthia, R., Francesca, D., “All Models are Wrong, but Many are Useful: Learning a Variable ’s Importance by Studying an Entire Class of Prediction Models Simultaneously,” Journal of Machine Learning Research, vol. 20, no. 177, pp. 1-81, 2019