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# An Empirical Investigation of Personalized Recommendation and Reward Effect on Customer Behavior: A Stimulus–Organism–Response (SOR) Model Perspective

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**Abstract:** With the continuous growth in the Home Meal Replacement (HMR) market, the significance of recommender systems has been raised for effectively recommending customized HMR products to each customer. The extant literature has mainly focused on enhancing the performance of recommender systems based on offline evaluations of customers' past purchase records. However, since the existing offline evaluation methods evaluate the consistency of products on the recommendation list with ones purchased by customers from the test dataset, they are incapable of encompassing components such as serendipity and novelty that are also crucial in recommendation. Moreover, the existing offline evaluation methods cannot measure rewards such as discount coupons that may play a vital role in strengthening customers' desire for purchase and thereby stimulating their purchase with a provision of a recommendation list. In this study, we used an SOR model to verify the effect of personalized recommendation stimulus on a customer's response in an actual online environment. The results indicate that the customers' response rate was higher with a provision of personalized recommendations than that of bestseller recommendations, and higher when being offered with cash discounts than earning redeemable points. Meanwhile, the response rate to the recommendation with higher volumes of rewards was not as high as expected, while the point pressure mechanism did not work either.

**Keywords:** personalized recommendation service; reward effect; SOR model; customer behavior; e-commerce platform

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## 1. Introduction

As modern people have started to give more attention to convenience followed by changes in their lifestyle, demand for Home Meal Replacement (HMR) has been continuously increasing. Accordingly, various food manufacturers have entered the HMR market to a greater extent, which has led to an expansion of such a market. Although customers' accessibility and convenience to HMR products have improved due to an annual release of numerous HMR products, search costs for gaining information have been generated during one's decision-making process. In other words, when it comes to choosing a product that perfectly suits one's preferences out of all, he or she often confronts the problem of information overload [1–3]. Although the demand for online shopping has increased after the COVID-19 outbreak, the information overload issue is still highlighted because customers have limitations in directly checking and experiencing their preferred products or services. Furthermore, from the corporate perspective, opportunities for promoting and exposing its products/services to customers are reduced, making it strenuous to generate profits. Considering ex ante circumstances, the significance of a recommendation system (recommender system) that could precisely recommend customized HMR products to an individual has been raised. In fact, global e-commerce companies such as Amazon [4], Netflix [5], and Google [6] are providing their own recommender systems that have in fact reinforced sustainable corporate competitiveness. For instance, Amazon generates 35% of its corporate revenue through sold products or services via its recommender system, while Netflix provides 75% of all contents viewed by customers through its recommender system [2]. As such, an effective recommender system can reduce the customer's information search cost and at the same time has a positive effect on corporate profit generation.

Most studies on recommender systems have focused on enhancing the recommender system performance using offline evaluations from customers' past purchase records [2,7–9]. Such a method is performed via a division of the customer's past purchase record data into the training and test dataset, while these two datasets are used to build a recommender system and to evaluate its performance, respectively [10–12]. However, since this method cannot cover actual online customers, there is a problem of identifying whether the recommended product worked as a stimulus for an individual to make his or her purchase. For example, in an actual online shopping environment, when online customers are provided with a list of recommended products, they decide whether to purchase a product included in the list. However, since the existing offline evaluation method checks the consistency of products from the recommendation list to the products purchased by customers retrieved from the test dataset, components such as serendipity and novelty that can affect the matter of recommendation cannot be evaluated. In other words, in an actual online shopping environment, there is a higher chance of having both preferred and unexpected products in the product recommendation list, such that they can potentially stimulate customers' purchases [13,14]. If one were to be provided with rewards on top of a recommendation list, they may act as a stimulus for one to purchase a good; however, such stimulating effect and one's purchasing desire are unmeasurable in offline experiments [15].

The Stimulus–Organism–Response (SOR) model is a model that systematically describes an organism's response to an external environment that affects an individual's cognitive and emotional states [16,17]. Here, a stimulus refers to an external factor, which represents for instance marketing mix; an organism refers to an internal process or structure such as an individual's emotions and feelings that intervene between the stimulus and the organism's response; and a response represents an external behavior due to the stimulus as well as the organism's internal reaction [18]. The SOR model is widely used to measure the effects of advertising and marketing, but numerous studies have mainly used a survey method to figure customers' response for the purpose of measuring the effect of an organism's response to stimuli. Particularly, there is a lack of research that considers recommendations and rewards as stimuli within the recommender system for investigating the effect of the customer's response in an actual online shopping environment.

The objective of this study is to incorporate the SOR model to verify the effect of personalized recommendation stimulus on the customer's response in an actual online environment. Many previous studies investigating the effect of customer response have collected data through surveys in offline environments to measure stimuli (e.g., recommendations and rewards). However, this study collected data from real-world e-commerce and conducted experiments in an actual online environment. Specifically, we try to identify the impact of the recommendations and rewards on customer purchase response. To this end, we first employ the SOR framework. In the context of the study, personalized product recommendation, an individual's positive emotions towards the recommended product, and one's purchase of the recommended product are regarded as stimulus, organism, and response, respectively. Based on this, we examine whether a product recommendation as the stimulus affects the customer's purchasing behavior. Such a stimulus was constructed based on both bestseller and personalized recommendations. In addition, as a means of enhancing the stimulus of personalized recommendations, we provided different types and sizes of rewards to investigate the impact on customers' buying behavior. This study conducted an experiment divided into two stages, shown in Figure 1. During the first stage, a personalized recommendation list was provided to 141 randomly selected customers out of all who purchased the product more than twice at C online shopping mall, while a bestseller recommendation list was instead provided to the other 140 to scrutinize whether personalized recommendations lead to the individuals' actual purchases. The second stage differentiates customers who participated in the first stage of the experiment into four groups based on either the types of rewards (discount vs. points earned) or the size (3000 won vs. 4000 won) to quantitatively measure the effect of recommendation according to the reward types or sizes. As a result, the response rate of individuals who received the personalized recommendation list was found to be higher than that of customers who received the bestseller recommendation list, which indicates that the personalized recommendation does act as stimulus. Moreover, as in previous studies, the response rate of individuals who received the personalized recommendation list and were offered a cash discount was higher than that of those who received the personalized recommendation list but earned points. However, it is worthwhile to note that the response rate to the recommendation was not high due to the larger amounts of rewards, which implies that the point mechanism for the reward does not work.

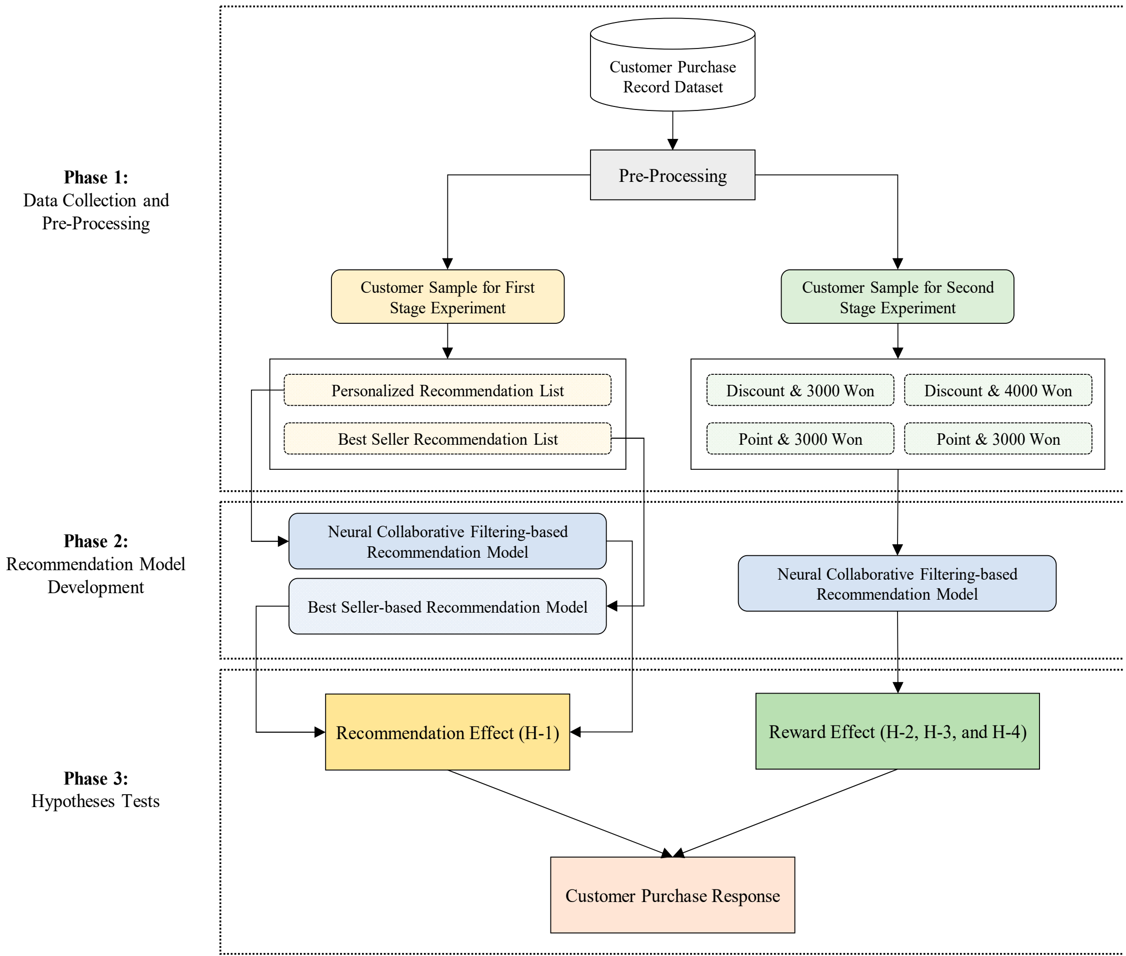



**Figure 1.** Research framework.

The following sections of this study are as follows. Section 2 presents the theoretical background and suggests the study's hypotheses. Section 3 encompasses the experimental methods such as the collection of data and the overall experimental design. Section 4 specifically describes the results of the tested hypotheses, while the last section covers the study's conclusion, implications, and future research.

## 2. Theoretical Background and Hypotheses Development

### 2.1. Food Recommender System

Most research on personalized recommendation services focus on developing recommender systems that consider customers' preferences by using preference ratings, purchase records, and behavioral patterns directly assigned by such customers [8,19,20]. Since the first introduction of the Tapestry recommender system by Goldberg, et al. [21], it also emerged in various fields regarding books [22–24], movies [25–28], music [29–31], as well as shopping malls [7,29,30]. Recently, as there has been a gradual expansion in the food market such as with HMR, research on food recommender systems has been widely conducted. Kadyanan, et al. [31] used the Item-based Clustering Hybrid Method (ICHM) and Slope One algorithms to improve the problem of recommending restaurants with few ratings. Kim, et al. [32] proposed a Markov Chain Model-based food recommender system by combining Sequential Association Rule Mining and Association Rule Mining, which showed better performance than bestseller-based as well as collaborative filtering recommender systems. Lee, Choi, Moon, and Kim [7] proposed a Recurrent Neural Network (RNN)-based food recommender system, showing a higher performance with many diverse products being recommended compared with collaborative-filtering-based recommendations from a multiterm perspective. Subramaniyaswamy, et al. [33] developed a health-oriented recommender system that can suggest food availability that considers climate attributes based on customers' personal choices and nutritional value. Such a recommender system is constructed via a customized filtering mechanism that combines ontology-based knowledge with Collaborative Filtering (CF) and Content-Based Filtering (CB). Mckensy-Sambola, et al. [34] developed a diet recommender system for overweight and obesity management using recipes and ingredients, which showed an accuracy of about 90% of advisors' proposals. Li, et al. [35] proposed a hybrid recommender system that combines content-based and collaborative filtering for the personalized recipe mobile applications. Mokdara, et al. [36] developed a recommender system using a deep neural network (DNN) for recommending a meal; the proposed model would extract the ingredients of interest from the recipe set of the customer's favorite dishes and evaluate the customer's profile with the DNN model after extracting features from the analysis of preferred ingredients. The system can also predict the next meal using a temporal prediction model regarding the customer's profile and meal records by collecting the past records of recipes that the customers selected.

In fact, most existing research on food recommender system use offline data, which corresponds to learned data based on a customer's past purchase records to generate a recommendation list. Then, it uses test data to evaluate such by examining how well the recommendation list matches the purchased products of the customer during the test period. However, there is a limitation of offline experiments disregarding serendipitous or novel products that can act as a possible stimulus for customers to make their next purchases. Therefore, it is of utmost importance to analyze whether the recommendation list of products acts as stimulus to affect the actual recommender system.

### 2.2. SOR Model

An individual is meant to respond to a given stimulus according to an appropriate behavioral pattern. The SOR model systematically describes an organism's response to an external environment which affects its cognitive, psychological state [16]. Here, a stimulus is an external, environmental factor which implies marketing mix [37]; an organism refers to an internal process or structure such as emotions and feelings intervening between the stimulus and response [37]; and a response represents an external behavior as a result of external stimulation and an organism's internal reaction [37].

Prior studies have explored various factors affecting one's behavioral intentions using an SOR model. Asl and Khoddami [38] investigated green purchase behavioral intentions with an SOR model that combines the theory of planned behavior and the theory of consumption values. The variables used for this research are as follows—perceived consumer responsibility, perceived consumer effectiveness, social norms, environmental visibility were used as the stimulus; emotional and social values were used as the organisms; green purchase intention and green purchase behavior were chosen as the response. To reinforce a theoretical understanding behind honeymoon tourism experiences, Chen, et al. [39] empirically investigated connections within its SOR model by setting perceived destination attributes as the stimulus, memorable tourism experiences and emotions as the organisms, and revisit intention and word-of-mouth intention as the response. Huang [40] used the SOR framework by setting active control and reciprocal communication/social identity as the stimulus, affective involvement and flow as the organisms, and cognitive involvement and purchase intention as the response to scrutinize the effect of social functions on virtual product purchase intentions in online settings such as social network websites. Kumar, et al. [41] inspected local food purchase behavior among members of a social-media-based local food distribution system with an SOR model, where altruism was set as the stimulus; supporting local producers, transparency, satisfaction with labeling, and desire as the organisms; and purchase intention as well as love towards the brand as the response. Ma, et al. [42] applied a SOR model to analyze the effect of online shopping experiences on customers' participation and online purchase intention under the circumstance of either weak or strong social bonds. Here, the online shopping experience was used as the stimulus, cognitive and emotional participation were used as the organisms, while online purchase intention was used as a response. Peng and Kim [43] used the SOR framework to investigate how consumers' hedonic shopping value, utilitarian shopping value, and environmental stimuli affect their repurchase intention, which mediates individuals' attitude toward online shopping and emotional purchase. Ric and Benazić [44] used interactivity as stimulus; motivation to use as an organism; and brand awareness and purchase intention as the responses to characterize the impact of 'likes', comments, and shared forms of interactions on consumer's shopping behavior.

One of the main purposes of advertising is to stimulate consumer purchasing behavior [45]. The extant literature has delineated that customer-generated advertisements enhance consumers' perceived information and reliability, which are proven to increase the effectiveness of advertisements compared with corporate-generated advertisements [46]. In other words, the quality of information affects a customer's satisfaction [47,48], which ultimately stimulates purchasing behaviors [48–50]. Likewise, the purpose of the recommender system is to increase the probability of customers purchasing products through a provision of items that suit their preferences. This implies that the accuracy of recommendation would increase with a higher quality of the recommender system. However, it is worthwhile to note that these studies have measured customers' responses mostly through surveys to evaluate the stimulus–response effects, while none of them have ever measured one's response by viewing recommendations and rewards as a stimulus and conducting online experiments to measure the response effects through the actual purchase results by customers.

In fact, the list of products presented to an individual through a personalized or bestseller recommender system acts as an external stimulus to the customer. This stimulus will form a positive or negative sensitivity to the recommended product through the customer's thought process. This customer's internal reaction will appear as one either purchasing or deciding not to purchase the recommended product. Since a personalized recommendation is generated based on the customer's product preferences, it will better suit his or her preferences than the bestseller version of the recommendation. Moreover, as the former uses other customers' preferences that are similar to one's preferences, it is possible to generate the list of products that are novel yet serendipitous compared with the mere bestseller recommender system. Therefore, the following hypothesis was established as follows.

**Hypothesis 1 (H1).** *Customers who receive a personalized recommendation list of products will have a higher purchase response rate than those who receive a bestseller-based recommendation list of products.*

*2.3. Loyalty Programs*

Loyalty programs are an integrated system of all marketing activities aimed towards an increase in product and service use, an induction of repurchase, and an expansion of loyal customers by providing tangible and intangible rewards based on the customer's product or service use [51]. In general, loyalty programs are branched into the continuity of a program, the nature of a program, the type of rewards, and the types of reward sponsors (see Figure 2) [52]. There are various options of how loyalty programs can be rendered as follows:

(1) Depending on the continuity of the program, the loyalty programs can be classified in a timely manner such as short-term or long-term loyalty programs.
(2) Loyalty programs can be classified based on the frequency of one's purchase or the amount spent per purchase, which depends on the nature of a program.
(3) Depending on the type of rewards, loyalty programs may provide either cash rewards such as actual cash and gift cards, or noncash rewards such as vacation coupons or prizes.
(4) Depending on the number of sponsors, loyalty programs can be divided into a single company being a sponsor or multiple companies sponsoring a reward program.

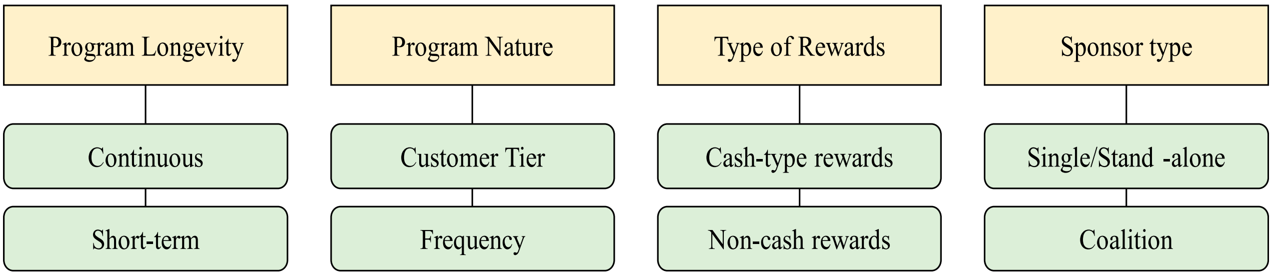



**Figure 2.** Loyalty programs classification.

Rewards have been widely introduced in numerous loyalty programs as an effective means of increasing customers' loyalty. However, the effectiveness of the reward program varies depending on the type of rewards being provided. Yi and Jeon [53] revealed that under the circumstance of high involvement, direct rewards that directly support the product's value proposition are found to be more valuable than indirect rewards that are not relevant to the product, while immediate rewards are found to be more valuable than the delayed rewards that are provided after the nth purchase under the circumstance of low involvement. According to Chandon, et al. [54], cash rewards are much more effective for utilitarian products than hedonic products. Therefore, when providing a list of recommended products, if rewards such as discount coupons and mileage accumulation were to be provided as well, the probability of product purchase will increase. For this reason, the hypothesis was established as follows.

**Hypothesis 2 (H2).** *Customers who receive a personalized recommendation list of products offering a cash discount will have a higher response rate to purchase than those who receive the same list but offering points as rewards.*

The size of the rewards also influences the effectiveness of the reward program. Despite the size of the rewards reducing the brand's loyalty [55,56], the effectiveness of the reward program increases as the size of the rewards increases [56–59]. Furthermore, although the size of the rewards leads to a better appeal of the loyalty program, it reduces the favorability of meta-perceptions recommended to other customers [59]. Therefore, in this study, the hypothesis was established as follows.

**Hypothesis 3 (H3).** *Customers who receive a personalized recommendation list with a large reward will have a higher purchase response rate than those who receive the same with a smaller reward.*

A representative reward program has the point pressure mechanism as shown in Figure 3 [60–63]. The point pressure mechanism is the effect of a reward program that provides rewards when a customer makes a purchase above a certain level (or purchase amount), which can increase the corporate sales volume. In other words, customers tend to make more purchases to surmount such constraints and receive rewards [61–64]. Based on this, the last hypothesis was established as follows.

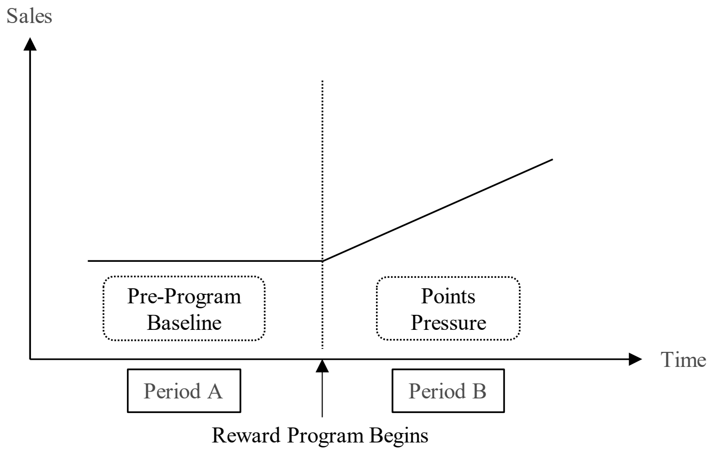



**Figure 3.** Points pressure mechanism.

**Hypothesis 4 (H4).** *Above a certain level or purchase, the amount of purchase rendered by one who receives a personalized recommendation list of products with a provision of rewards will be higher than that of one with the same list of recommendation but with the rewards.*

## 3. Research Methodology

### *3.1. Study Design*

In this study, using the SOR framework, the effect of personalized recommendation service was examined through an online experiment determining the matter of purchase followed by a provision of a product recommendation list for each customer from C online shopping mall selling HMRs. Both personalized and bestseller recommendations were set as the stimulus, while we presumed that the organism would carry positive emotions during the purchase. Here, the response was set as the purchase of the recommended product. We aimed to compare the purchase response between individuals who are provided with a personalized recommendation list and those with a bestseller recommendation list to seek for the effect due to the personalized recommendation acting as a stimulus. We also investigated how much the effect of recommendation increased when rewards were provided on top of the personalized recommendation list; we varied the type and size of rewards to explore such. To achieve such a goal, during the first stage of our experiment, we provided both personalized and bestseller recommendation lists to customers who bought a product more than twice to evaluate whether a personalized recommendation acts as stimulus. Next, to measure the effect of rewards, the second stage of the experiment was conducted against the same subjects as the above, but now divided into four different groups depending on the types (discount vs. points) and the sizes (KRW 3000 won vs. 4000 won) of rewards. Since it was free in delivery fee if the amount of purchase was more than 30,000 won, the baseline was set at 40,000 won to measure the effect of point pressure.

### 3.2. Data Collection and Preprocessing

In this study, customer purchase record data were collected from the shopping mall C that specializes in HMR products. We first developed our recommender system using such data that ranged from 1 July 2019 to 31 December 2021 to evaluate its performance. Among them, the training dataset included 3792 purchase records data over 208 products and 535 customers from 1 July 2019 to 30 September 2021 for building the recommender system. Meanwhile, 152 purchase records data, including 70 customers and 75 products collected from 1 to 28 December 2021, were used as validation data. Next, the data from 28 February to 27 March 2022 were used for the first stage of this study's experiment, while the data from 1 to 28 April 2022 were used for the second stage of the experiment. As shown in Figure 4, to determine whether personalized recommendations stimulated one's purchase during the first stage of the experiment, 281 customers were randomly selected among all customers who made their purchase more than twice, where 141 were given the personalized recommendation list while the other 140 customers were given the bestseller recommendation list. In the second-stage experiment, the number of people included in each group was 70 each, but 31 customers canceled their membership during the first stage; thus, the experiment was conducted on a total of 249 customers.

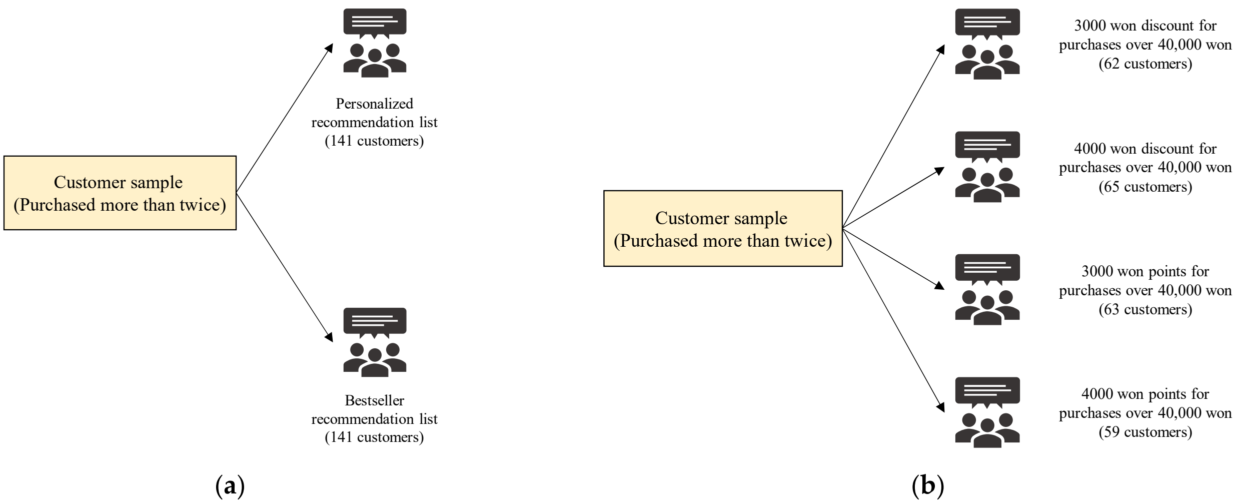



**Figure 4.** (**a**) Customer sample for first stage experiment; (**b**) customer sample for second stage experiment.

### 3.3. Recommendation Model Development

To provide a personalized product recommendation list for each customer, we constructed User-Based Collaborative Filtering (UBCF) and Neural Collaborative Filtering (NCF) models that have been widely used in existing studies to be compared [10,65]. We decided to select one of the presented techniques that demonstrates higher performance for providing the recommendation list to customers. For UBCF, its recommendation procedure consists of the stages of forming a group of customers with similar preferences and building a recommendation list. This indicates that UBCF formulates a recommendation list for a targeted customer based on the group who shares similar preferences [65]. On the other hand, NCF is intended to extract nonlinear relations through an application of DNN to disclose the interactions between a customer and product in an effective manner [66]. It works by converting the embedding layer containing information of both the customer and product into latent vector. Specifically, the Multilayer Perceptron (MLP) layer computes the nonlinear relationship between the customer and product by passing the latent vector of the customer and product through its layer [66]. In the end, the output layer predicts the probability of a customer purchasing a particular product based on the results calculated in the previous layer. In this study, the F1 score, an indicator mainly introduced in classification-related studies, was used to measure the performance of the recommender model [12,65]. As a result, it was confirmed that the recommendation performance of the NCF model was about 85.22% and 79.32% better off, compared with the UBCF recommendation algorithm and BS, respectively. Therefore, in this study, a personalized recommendation list was provided to customers using the NCF model. Based on this, the personalized recommendation product list and rewards sent to the customer are shown in the example of Figure 5.

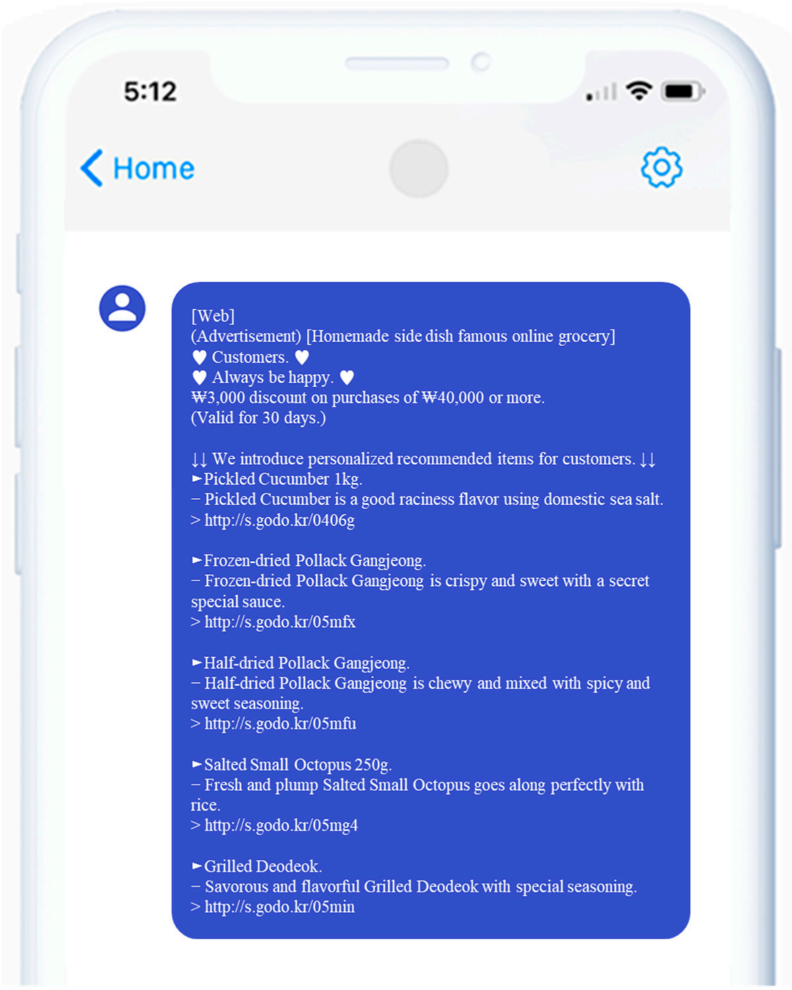



**Figure 5.** Sent message examples of personalized product recommendation lists and rewards.

## 4. Hypotheses Tests

### *4.1. Impact of Recommendation Method on Customer Behavior*

The results of the online experiment can be witnessed in Figure 6. In fact, the response rate of customers who received a personalized recommendation list of products was 10.6%, which was approximately 3.5 percent higher than that of those who received a bestseller recommendation product list (7.1%). Thus, hypothesis 1 was accepted.

For the amount per single purchase of an individual, it was 44,990 won for the one who received the personalized recommendation list, which was 2455 won less than the number of purchases made by the one who instead received the bestseller recommendation list. An additional analysis was conducted to verify whether the difference in these purchase amounts according to the method of recommendation was statistically significant. Since the amount of purchase according to the recommended method did not satisfy the normality, a Mann–Whitney U test as a nonparametric method was conducted, where its results are shown in Table 1. The value for the Mann–Whitney U test was found to be 85.000 for the difference between the purchase amount of the customer who received the personalized recommendation list and the bestseller recommendation list with the $p$-value of 0.398. Therefore, the difference between these two groups is statistically the same.

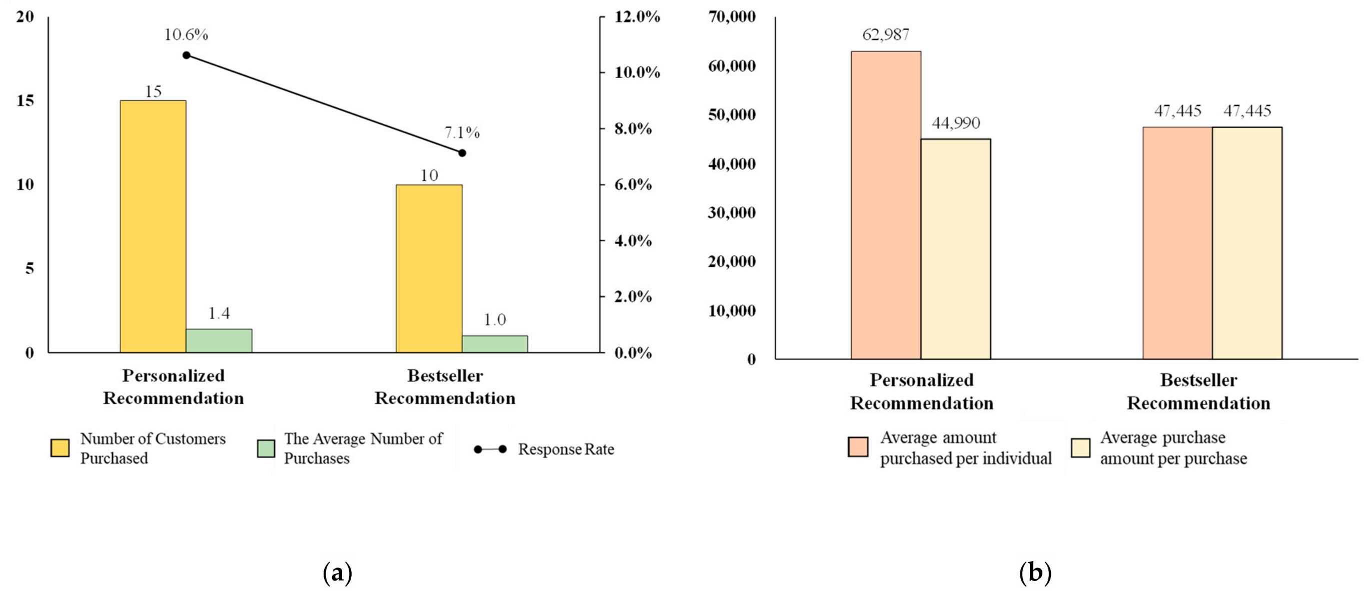



**Figure 6.** Comparison of purchase effects of personalized and bestseller recommendations. (**a**) Response rate; (**b**) amount of purchase.

**Table 1.** Mann–Whitney U test results for the difference in purchase amount on recommendation method.

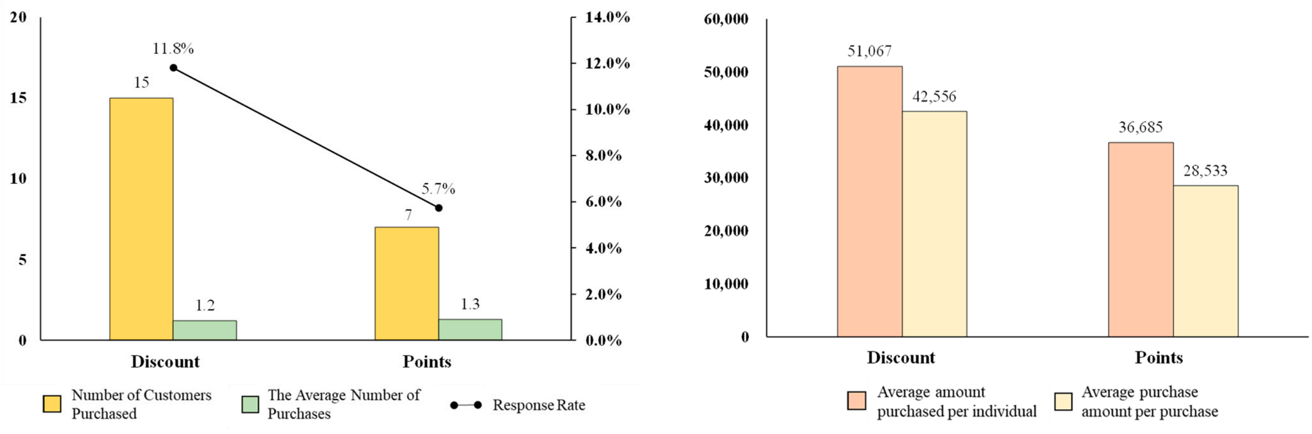
| Recommendation Method | N | Mean Rank | U | W | Z | P |
|---|---|---|---|---|---|---|
| Personalized Recommendation | 10 | 18.00 | 85.000 | 316.000 | −0.845 | 0.398 |
| Bestseller Recommendation | 21 | 15.05 | | | | |

*4.2. Impact of Reward on Customer Behavior*

4.2.1. Recommendation Effect based on the Reward Type

The results after comparing the purchase response rate of customers by the reward type are shown in Figure 7. The response rate of customers who received a personalized recommendation product list with cash discounts was 12.6%, which is 6% higher than that of those who received the same list but with redeemable points (6.6%). Moreover, when looking at the proportion of customers who purchased more than 40,000 won, 60.0% accounted for customers who received a personalized recommendation list with cash discounts, while 28.6% received a personalized recommendation list with redeemable points. Thus, hypothesis 2 was accepted.

Considering the amount of a single purchase per customer by the reward type, it was revealed that the purchase amount of the customer who received the cash discount was 42,556 won, which was 14,023 won higher than the purchase amount (28,533 won) of the customer who received the redeemable points. Table 2 shows the results of the Mann–Whitney U test for verifying whether the difference in the amount of purchase according to the reward type had a statistical significance. In fact, the Mann–Whitney U value turned out to be 74.000 with regard to the difference between the purchase amounts of the customer who received the redeemable points and cash discounts, where the $p$-value was 0.075. In other words, there was a statistical difference in the amount of purchase between these two groups at the significance level of 0.1.




(**a**) (**b**)

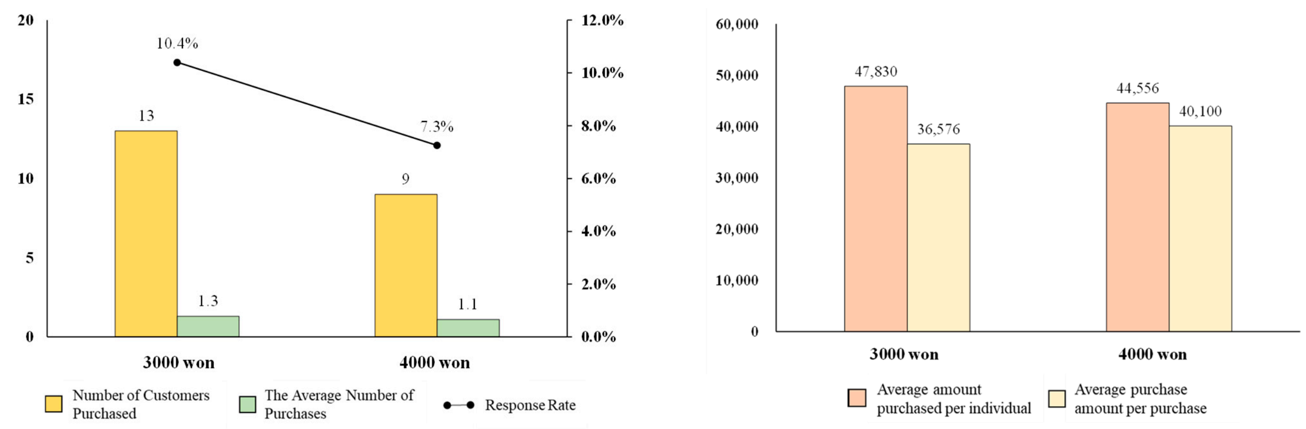
**Figure 7.** Comparison of purchase effects of recommendation services by reward type. (**a**) Response rate; (**b**) amount of purchase.

**Table 2.** Mann–Whitney U test results for the difference in purchase amount on reward type.

| Reward Type | N | Mean Rank | U | W | Z | P |
|---|---|---|---|---|---|---|
| Points | 9 | 8.22 | 74.000 | 74.000 | −1.778 | 0.075 |
| Discount | 12 | 13.08 | | | | |

### 4.2.2. Recommendation Effect based on the Reward Volume

The results of comparing the customer's purchase response rate by the reward volume is shown in Figure 8. The response rate of customers who received a personalized product recommendation list with a reward of 3000 won was 10.4%, which was 3.1% higher than that of those who received the same with a reward of 4000 won (7.3%). In terms of the proportion of customers who purchased more than 40,000 won, 53.8% of customers were ones who received a reward of 3000 won, while 44.4% of customers accounted for ones who received a reward of 4000 won. Thus, hypothesis 3 was rejected.




(**a**) (**b**)

**Figure 8.** Comparison of purchase effects of recommendation services by reward volume. (**a**) Response rate; (**b**) amount of purchase.

When observing the amount spent per single purchase by the reward amount, we figured that the purchase amount spent by the one who received the reward of 3000 won was 36,576 won, which was 3524 won less than the one who received the reward of 4000 won (40,100 won). Table 3 displays the results of the Mann–Whitney U test to verify whether the difference in the purchase amount according to the reward amount was statistically significant. It turned out that the Mann–Whitney's U value was 99.500 for the difference between the purchase amount of the customer who received the reward of 3000 won and the amount spent by the customer who received the reward of 3000 won, where its *p*-value was 0.466.

**Table 3.** Mann–Whitney U test results for the difference in purchase amount on reward volume.

| Reward Volume | N | Mean Rank | U | W | Z | P |
|---|---|---|---|---|---|---|
| 3000 won | 17 | 13.15 | 99.500 | 154.500 | 0.728 | 0.466 |
| 4000 won | 10 | 15.45 | | | | |

4.2.3. Recommendation Effect based on the Reward Type and Volume

Figure 9 shows the results that compare the response rates of an individual purchasing a product by the reward type or volume. The response rate of the customers who received a personalized recommendation list with a discount of 3000 won, a discount of 4000 won, redeemable points of 3000 won, and redeemable points of 47,000 won were 12.9%, 10.8%, 7.9%, and 3.4%, respectively. Here, it is observable that the response rate of customers who received the discount of 3000 won on top of the recommendation list was the highest. Furthermore, in terms of the proportion of customers who spent more than 40,000 won, the customers who received a discount of 3000 won, a discount of 4000 won, redeemable points of 3000 won, and redeemable points of 4000 won were 75.0%, 42.9%, 20.0%, and 50.0%, respectively.

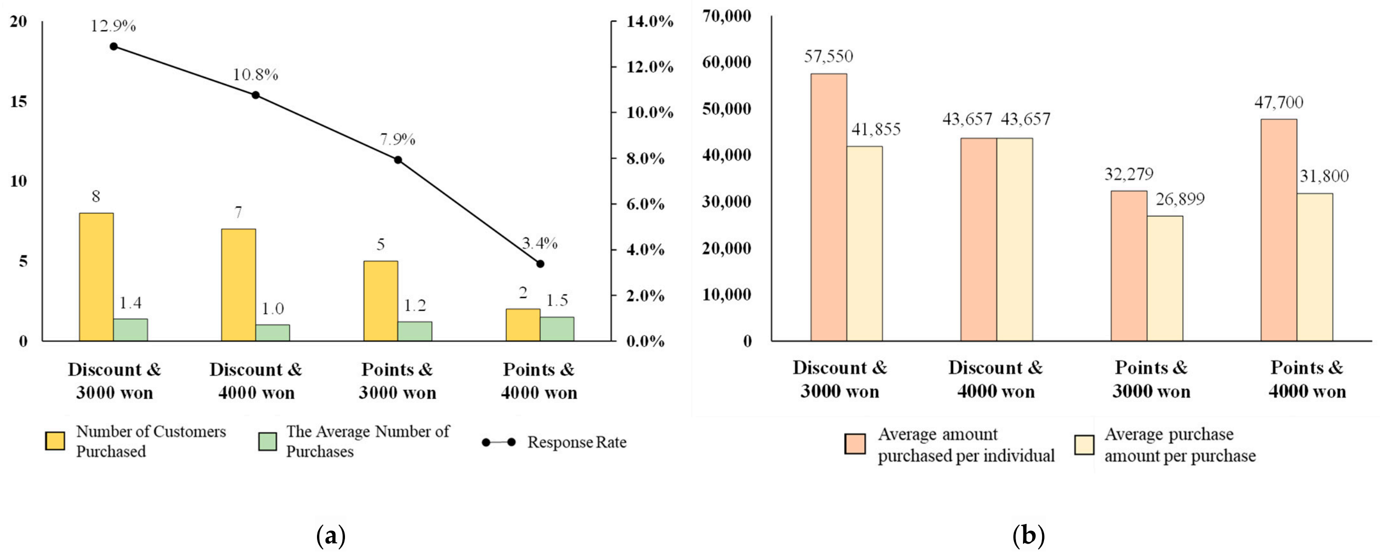



**Figure 9.** Comparison of purchase effects of recommendation services by reward type and volume. (**a**) Response rate; (**b**) amount of purchase.

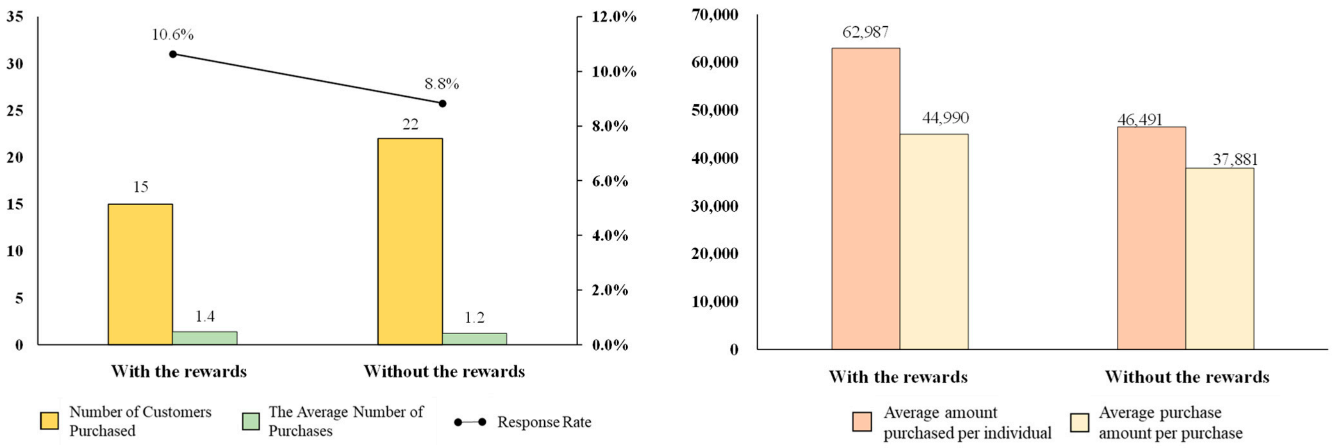
In terms of the amount spent per single purchase according to the reward type and volume, the amount of purchases by the one who had a discount of 3000 won was 41,855 won; the amount of purchase by the one who had a discount of 4000 won was 43,657 won; the amount of purchases by the one who received 3000 won of redeemable points was 26,899 won; and the amount of purchases by the one who received 4000 won of redeemable points was 31,800 won. Here, we could witness that the amount spent for a single purchase was the highest for those who were provided with a cash discount of 4000 won. Therefore, a Kruskal–Wallis H test was conducted to verify whether the difference in the purchase amount according to the reward amount was statistically significant as demonstrated in Table 4. The H value of the Kruskal–Wallis test for the difference in the purchase amount of each group turned out to be 74.000 with the *p*-value of 0.280.

**Table 4.** Kruskal–Wallis H test results for the difference in purchase amount on reward type and volume.

| Reward Type and Volume | N | Mean Rank | H | df | P |
|---|---|---|---|---|---|
| Discount and 3000 won | 11 | 15.14 | 74.000 | 3 | 0.280 |
| Discount and 4000 won | 7 | 17.36 | | | |
| Points and 3000 won | 6 | 9.50 | | | |
| Points and 4000 won | 3 | 11.00 | | | |

#### 4.2.4. Recommendation Effect based on the Point Pressure

As a matter of fact, companies offer free delivery to customers who spend more than 30,000 won during their online experiments. In this study, the baseline was set at 40,000 won to take into account the point pressure mechanism. The results of comparing the customer's purchase response rate to the point pressure are shown in Figure 10. The response rate of customers who received the personalized recommendation list of products without any rewards was 10.6%, which is 1.8% higher than the response rate of customers who received the personalized recommendation list with the rewards (8.8%).




(**a**) (**b**)

**Figure 10.** Comparison of purchase effects of recommendation services by point pressure. (**a**) Response rate; (**b**) amount of purchase.

In terms of the amount spent per purchase by each group, individuals who received the personalized recommendation list without the rewards spent 44,990 won, while those who received the list with the rewards was 37,881 won. Table 5 contains the results of the Mann–Whitney U test for verifying the statistical significance in the difference between the purchase amounts when the reward was provided or not. It was found that the U value of the Mann–Whitney test turned out to be 245.000 with the *p*-value of 0.424. Therefore, there was no statistical difference in the purchase amount between the two groups. In other words, there was no difference in the amount of purchase per customer regardless of the reward provision. Hypothesis 4 was therefore rejected.

**Table 5.** Mann–Whitney U test results for the difference in purchase amount on point pressure.

| Point Pressure | N | Mean Rank | U | W | Z | P |
|---|---|---|---|---|---|---|
| With the rewards | 27 | 23.07 | 245.000 | 623.000 | −0.800 | 0.424 |
| Without the rewards | 21 | 26.33 | | | | |

## 5. Discussion and Conclusions

### 5.1. Conclusions

Recently, there has been a rapid growth in the HMR market due to an increase in single-person and double-income households, the prevalence of air fry, the growth of convenience stores, as well as the outbreak of COVID-19. Accordingly, many companies have entered the HMR market, leading to a dramatic increase in the retails of HMR products such as meal kits through online shopping malls. As a matter of fact, online shopping malls have endeavored to gain a competitive advantage by introducing a recommendation system for customers to make them less difficult for choosing items that suit their preferences. Researchers in the field of recommendation systems have developed various methodologies such as CF, CB, and NCF; however, most of these methods are used for offline experiments that evaluate the effect of the recommendation system. Since offline experiments determine a matter of purchase suiting one's preferences if a recommended product is found in the test data, factors such as accidental luck and the novelty of the recommended product are not considered at all. In other words, there is a chance of an individual receiving the recommendation list that not only includes his or her preferred products, but also unexpected ones that could potentially stimulate the customer's purchases. Moreover, when providing a list of recommended products, one's buying desire can be reinforced with the provision of rewards acting as an additional stimulus. Therefore, in this study, an online experiment was conducted to measure the effect of personalized recommendation services based on the SOR framework. The stimulus was set to both personalized and bestseller recommendations, while the organism was considered to have a positive emotion during the purchase, which was set as a response.

The results of this study are shown in Table 6. Firstly, the response rate of an individual who received the personalized recommendation list was higher than that of one who was given the bestseller recommendation list. It is therefore discernible to claim that the former list consists of products that are not only personalized but also novel yet serendipitous and acted as a stimulus to one's purchase, causing positive emotions. Thus, hypothesis 1 was accepted. However, there was no statistical difference in the amount spent per purchase between the two groups.

**Table 6.** Summary of experiment results.

| | Hypotheses | Result |
|---|---|---|
| H1 | Customers who receive a personalized recommendation list of products will have a higher purchase response rate than those who receive a bestseller-based recommendation list of products. | Accept |
| H2 | Customers who receive a personalized recommendation list of products offering a cash discount will have a higher response rate to purchase than those who receive the same list but offering points as rewards. | Accept |
| H3 | Customers who receive a personalized recommendation list with a large reward will have a higher purchase response rate than those who receive the same with a smaller reward. | Reject |
| H4 | Above a certain level or purchase, the amount of purchase rendered by one who receives a personalized recommendation list of products with a provision of rewards will be higher than that of one with the same list of recommendations but with the rewards. | Reject |

Secondly, the response rate of the customer who received the personalized recommendation list with the cash discount was higher than that of one who received the recommendation list with redeemable points. We ascertained that cash discounts, compared with redeemable points, promote purchases for personalized recommendation services. Thus, hypothesis 2 was accepted. In terms of the amount of purchases made by the reward type, it was found that the amount spent by the one who received the discount was statistically higher at the significance level of 10% than the amount spent by the one who received the redeemable points instead. Therefore, it is assertable that customers who receive the cash discount are likely to spend more money than those who receive the redeemable points.

Thirdly, the response rate of the customer who received the personalized recommendation list with a reward of 3000 won was higher than that of the one with a reward of 4000 won. It is unreasonable to claim that the reward volume plays a role in promoting one's purchase. Thus, hypothesis 3 was rejected. Moreover, it was found that there was no statistical difference in the purchase amount of the two groups. Therefore, there was no statistical difference in the purchase amount of the two groups, which implies that there was no difference in the amount spent per purchase according to the reward size.

Fourthly, the customer response rate of those who received the personalized recommendation list with a discount of 3000 won was the highest. In comparison, the proportion of customers who received a discount of 3000 and 4000 won showed a higher response rate than those who received the same amounts of redeemable points out of all customers who purchased more than 40,000 won. It is, therefore, valid to insist that the type of reward has a better hand in promoting one's purchase than the size of the rewards. Seeing the amount spent per single purchase by each reward type and size, there is no statistical difference in the purchase amount between such groups. The results reflect that there is no statistical difference in the purchase amount of each group, implying that there is no difference in the amount spent according to the reward type and size.

Finally, the response rate of the customer who received the personalized recommendation list without rewards was higher than that of the one given the rewards. At the same time, there was no difference in the purchase amount per customer, regardless of the reward provision. This was because even if rewards are provided when one decides to purchase above a certain level, there is a limit for one to hold a certain amount of inventory at home, considering the characteristics of HMR products distinctly having an expiry date. Thus, hypothesis 4 was rejected.

### *5.2. Theoretical and Practical Implications*

The theoretical contributions of this study are as follows. First, the existing SOR framework was limited to the individual level, and limited data collection was conducted mainly based on questionnaires. However, with the development of IT technologies, including the Internet, market-level data are collected in various fields. To utilize the data that contain the phenomenon of the entire market, it is necessary to apply various theories at the market level. This study contributes to expanding the SOR framework to the recommendation domain of e-commerce. Second, as the types of products have been diversified and the number of customers has increased, the transactional data size has been dramatically increased, and the data type has also diversified. Therefore, the existing CF-based recommendation algorithms are suffering from sparsity and scalability problems. In e-commerce, it is necessary to quickly find recommendation items using real-time information and provide personalized recommendations to each customer. This study developed a deep-neural-network-based model that recommends products or services to customers in real time to measure the effectiveness of personalized recommendation services based on the SOR framework. The results showed that the personalized recommendation list of products that match the customer's preferences and new and unexpected products is a stimulus causing one's purchases. Third, many studies have revealed that the point pressure mechanism works in loyalty programs, which is not the case for the HMR market.

This is possible because of the shorter lifespan of HMRs compared with other products, which may delimit customers from holding many HMRs in stock at once.

The practical implications of this study are as follows. First, most shopping malls tend to recommend best-seller products to customers, and this is because they believe customers are satisfied when they recommend products or services that have been purchased a lot. However, customers will be less satisfied if they are recommended similar products or services each time. This study has indirectly confirmed that customers in the HMR market are more interested in recommended products that match their preferences than best-seller products. Therefore, HMR shopping malls need to display products that match one's preferences on the main web page when they log in. Second, it has been verified that customers in the HMR market prefer cash discounts over redeemable points. This study suggests the need to rethink existing business strategies by statistically verifying that cash discounts affect customer purchase behavior. In other words, if an HMR shopping mall would want to proceed with its loyalty program, it is discernible to consider a cash discount as a reward to be provided. Third, although the extant literature has demonstrated that the size of rewards increases one's purchase intention, it is not applicable in the HMR market as the size of the rewards did not affect the customers' purchase. Therefore, if an HMR shopping mall were to keep its loyalty program, it would be much more effective to offer a cash discount, even if it is pretty small, rather than offering different rewards.

### *5.3. Limitations and Future Research*

This study has the following limitations. First, to conduct and evaluate online experiments, it is necessary to include a larger number of online customers as the study subjects. However, considering the amount of time and cost limited for the study, the experiment could only be conducted against 280 customers, so it is essential to bring more subjects and aim for generalization. Second, we used cash-related rewards such as discount and redeemable points to be earned as the type of rewards. However, it is worthwhile to recognize that cash rewards can be much more diverse, which could involve for instance prizes, while there are also noncash rewards. Therefore, there is a need to verify the effect of rewards from a diverse pool. Third, we set the size of the rewards into 3000 won and 4000 won to measure the effect of the recommendation according to the reward size. Since the difference between such reward amounts is not large, the effect may not quite appear. Therefore, future research can further evaluate the effect of recommendations where there are more options of reward amounts provided. Fourth, in this study, the baseline was set at 40,000 won to explore the point pressure effect. However, HMR customers spend about 30,000 won to 50,000 won for a single purchase. This can act as a direction for future studies to diversify the baseline to draw inferences on the point pressure effect.

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