

# A HYBRID DEEP RECOMMENDATION SYSTEM FOR ISSUING DIGITAL COUPONS IN REAL-TIME

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In the field of marketing, offering discount coupons to encourage purchases is one of the most frequently used strategies. In particular, with the rise of online shopping malls surpassing offline ones, digital coupons have become increasingly prevalent. The key challenge in issuing coupons is identifying customers with a high risk of churn and providing them with coupons of the right category at an optimal discount rate. Manually addressing this task is impractical because online shopping platforms serve millions of users and offer a wide variety of coupon types. Accordingly, this study proposes a time series deep learning framework that identifies customers at high risk of churn in real time and provides them with personalized coupons for relevant product categories at appropriate discount rates. To address the data class imbalance problem, additional dependent variables were introduced, and static customer meta-information was combined with real-time page click features to enhance accuracy. In addition, we tested the improvement in financial profits of an actual shopping mall. After various ablation model experiments, the results show the superiority of our proposed framework, which has brought great profits to the platform. The proposed framework achieved an AUC of 0.747 for purchase intention prediction, improved coupon conversion rates by up to 32.65%, and increased the relative profit index from 100.0 to 103.15 in real-world deployment experiments.

**Keywords:** Deep Recommendation System; Digital Marketing; Clickstream Analysis; Purchase Intention Detection; Churn Prediction; Coupon Discount Optimization

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## 1. INTRODUCTION

In the realm of marketing, inducing purchase by issuing discount coupons is one of the most commonly used methods (Lewis, 2004). In particular, the issuance of coupons in digital format has become common recently as online shopping malls outperform offline ones. Compared to offline coupons, digital coupons can utilize a large amount of online data and have the advantage of being issued in real time. As the e-commerce market intensifies, competition for promoting the purchase by coupon strategies is intensifying (Hu *et al.*, 2023).

The biggest issue in digital coupon issuance is maximizing spending by understanding customer preferences at the lowest cost. To do this, three issues need to be considered. (1) Customers' tastes must be identified, and digital coupons for customized products or categories must be issued. Issuance of random product coupons that do not consider the customer's taste may rather encourage customers' antipathy and reduce their loyalty to the shopping mall. This can be solved by analyzing behavioral pattern data that the customer has shown in the shopping mall in the past. (2) Coupons should be issued to customers with a high risk of churn. Excessive issuance of coupons to customers who are already willing to purchase can actually lower the profit of the shopping mall. In addition, if coupons are excessively used, customers may rather harbor resentment when coupons are not issued. This can be solved by time-series analysis of click patterns where customers act on the platform in real time. (3) Coupons must be issued within the set budget. Excessive issuance of coupons can increase the purchase conversion rate, but can decrease profit. In addition, it is necessary to optimize the discount rate of coupons to an appropriate level. This can be done by adjusting the coupon discount rate in the direction of optimizing profit against the purchase conversion rate. Here, the purchase conversion rate refers to the proportion of coupon recipients who completed a purchase after coupon issuance. In contrast, profit optimization

additionally considers discount costs and margin preservation. Therefore, higher conversion rates do not necessarily imply higher profitability.

First of all, it is possible to estimate whether or not a coupon should be issued by identifying the customer's real-time purchase intention. However, identifying purchase intention is a difficult task. E-commerce platforms are complex, and numerous variables must be considered to accurately identify customers' purchase intentions. For example, simply coming to see a product detail page does not necessarily mean that there is a purchase intention. Someone can simply browse the product detail pages and leave. Therefore, it is necessary to create a purchase intention estimation model by comprehensively considering various variables. However, a data label imbalance problem occurs when building training data for supervised learning to create an estimation model. Most of the customers on the e-commerce platform leave without purchasing. It is known that the average purchase conversion rate in e-commerce platforms is around 2% (Stadnik *et al.*, 2018). Therefore, this data label imbalance problem should be considered during supervised learning. Usually, Synthetic Minority Over-sampling Technique (SMOTE) or cost-sensitive learning is used to solve class imbalance. However, these methods are not suitable when classes are extremely unbalanced, such as in this study (purchase class/churn class). In extremely unbalanced cases, the original minority class data itself is very small, so the generated samples are too similar to existing samples or the penalty for misclassifying the data is too large. In this study, we developed a deep learning model that simultaneously estimates both the probability of purchase and the probability of stay. The model was designed with a focus on the conditional relationship that a stay is a prerequisite for a purchase. This approach helps address the data imbalance issue that arises when predicting only the probability of purchase, where purchase data is relatively scarce compared to non-purchase data.

The variables used for estimating the purchase probability are divided into real-time characteristics and static characteristics. Variables with real-time characteristics are time-series page click stream data on the platform in real time, and variables with static characteristics include purchase history and customer demographic information. The deep learning model was improved by learning time-series properties through combining the attention model with LSTM (long short-term memory).

Second, in order to optimize coupon allocation, coupons of customized categories were issued with consideration of customers' tastes. We applied a content-based filtering algorithm that recommends the product group that the customer is most interested in by analyzing the customer's purchase history. To enhance recommendation diversity, we integrated collaborative filtering, which suggests product groups purchased by customers with similar preferences.

Third, the discount rate was optimized for each user. Using a deep learning model, the coupon discount rate was adjusted in the direction of maximizing profit.

The novelty of this study lies not in the isolated algorithms themselves but in the unified real-time integration of three heterogeneous modules — (1) dual-task purchase intention estimation, (2) recommendation with dynamic preference fusion, and (3) profit-driven coupon allocation optimization — into a single deployable pipeline operating on real-time clickstream data. Unlike previous works that evaluate each sub-model separately, our approach jointly trains and synchronizes all three stages, allowing information such as churn likelihood and coupon sensitivity to interact adaptively. This integration bridges the gap between academic models and real-world e-commerce deployment by demonstrating measurable profit improvement in an operational shopping mall.

From an industrial engineering perspective, the proposed framework can also be interpreted as a real-time constrained resource allocation and operational decision system, where limited coupon budgets are dynamically allocated across heterogeneous customer sessions under uncertainty. Unlike conventional static optimization approaches, the framework continuously synchronizes behavioral prediction, recommendation, and economic optimization within a deployable online decision pipeline.

## 2. LITERATURE REVIEW

This digital coupon issuance study was conducted based on previous research in the four categories below. Prior research on issuing coupons for preferred product groups (A. personalized recommendations for customers), prior research for selecting customers with purchase/churn probability (B. Customer intention analysis), prior research for selecting the optimal coupon discount rate (C. knapsack problem), and prior research for understanding customers' purchasing motivation (D. Buying signs page clickstream analysis) are summarized. A detailed summary of these prior studies, including key methodologies and findings, is provided in Table 1.

Table 1. Research literature

| Research                      | Research Focus                                                   |
|-------------------------------|------------------------------------------------------------------|
| Childers <i>et al.</i> (2001) | Hedonic and utilitarian motivations for online shopping          |
| Linden <i>et al.</i> (2003)   | Amazon item-to-item collaborative filtering                      |
| Dittmar <i>et al.</i> (2004)  | Gender differences in online and conventional buying motivations |
| Kellerer <i>et al.</i> (2004) | Multiple-choice knapsack problem for discount optimization       |
| Zhou <i>et al.</i> (2008)     | Netflix Prize large-scale collaborative filtering                |

| Research                       | Research Focus                                                      |
|--------------------------------|---------------------------------------------------------------------|
| Felfernig <i>et al.</i> (2008) | Constraint-based recommender systems                                |
| Verhagen and van Dolen (2011)  | Influence of online store beliefs on impulse buying                 |
| Park and Kim (2012)            | Multi-category product recommendation for preventing customer churn |
| Kim <i>et al.</i> (2016)       | Intent detection using semantically enriched word embeddings        |
| Nielsen <i>et al.</i> (2017)   | Sampling bias in developmental psychology studies                   |
| Wang <i>et al.</i> (2018)      | Bi-model RNN for intent detection and slot filling                  |
| Tarus <i>et al.</i> (2018)     | Ontology-based recommender systems for e-learning                   |
| Guo <i>et al.</i> (2018)       | Urban data-based store site recommendations                         |
| Xia <i>et al.</i> (2018)       | Zero-shot user intent detection using capsule networks              |
| Chen <i>et al.</i> (2019)      | Time-aware smart object recommendation in IoT                       |
| Sahoo <i>et al.</i> (2019)     | Deep learning-based health recommendation system                    |
| Khattak <i>et al.</i> (2023)   | Composite deep learning techniques for customer churn prediction    |
| Manzoor <i>et al.</i> (2024)   | Machine learning methods for customer churn prediction              |
| Ako <i>et al.</i> (2024)       | Effects of data resampling on customer churn prediction             |

### 2.1. Personalized recommendations for customers

Customer preference analysis is a long-researched topic in the e-commerce area. In particular, the advancement of online platforms has streamlined customer log collection, making it easier to analyze individual preferences. In the past, recommendations based on an individual's purchase history, recommending related items or items that other people purchased a lot together was mainly used (Park and Kim, 2012). After that, large platforms such as Amazon and Netflix made customized recommendations using collaborative filtering techniques (Linden *et al.*, 2003; Zhou *et al.*, 2008). Other types of recommendation system like Knowledge-based recommendation systems and constraint-based recommendation system are also used (Tarus *et al.*, 2018; Felfernig and Burke, 2008).

### 2.2. Customer intention analysis

Detecting user intent refers to predicting which intent corresponds best to a user request. The problem of user intent detection has been heavily studied in the machine learning community (Fang, 2024). In particular, in the case of online platforms, it is possible to store large amounts of data in real time, so it is possible to analyze customer behavior patterns based on machine learning.

Authors present a word embedding method to improve the intent detection task (Kim *et al.*, 2016). In Xia *et al.* (2018), Capsule Neural Networks are used to detect emerging user intents where no labeled utterances are currently available. Wang *et al.* (2018) proposed a bi-model-based recurrent network to perform the intent detection and slot filling tasks jointly.

With the rapid development of e-commerce, user purchasing intent detection on e-commerce platforms is also a promising research field. Basically, given a user-click session, the goal of purchasing intent detection is to predict whether the user is going to place an order (Koehn *et al.*, 2020; Seo and Yoo, 2023). Recently, there has been an increasing number of studies estimating customer churn rates in e-commerce (Manzoor *et al.*, 2024; Ako *et al.*, 2024; Khattak *et al.*, 2023). This is because large-scale, real-time data processing has become possible, making research using this approach easier. This study differs from prior research by conducting practical experiments that directly evaluate profit improvement in actual e-commerce settings. In addition to identifying customers with a high risk of churn, this study also explores coupon issuance strategies designed to enhance overall shopping mall profitability.

Furthermore, transformer-based sequential recommendation models such as SASRec (Kang, 2018) and BERT4Rec (Sun *et al.*, 2019) have demonstrated strong performance in behavioral sequence modeling by capturing long-range dependencies within user interaction sequences. However, these models generally require substantially larger computational resources and inference costs compared to lightweight recurrent architectures. In real-time coupon issuance environments where low latency and operational scalability are critical, lightweight LSTM+Attention architectures remain practically attractive for deployable industrial systems.

In this study, the probability of a user's purchase was estimated by LSTM-Attention-based time series analysis of real-time clickstream data. By analyzing the order of real-time page views, customers' hidden intentions were estimated, and purchase/churn customers were selected. In addition, customized discount coupons are issued to customers with a high risk of churn. Therefore, accurately estimating purchase intention is the first and most important process.

### 2.3. Knapsack problem

The knapsack problem is the following problem in combinatorial optimization. The problem often arises in resource allocation where the decision-makers have to choose from a set of non-divisible projects or tasks under a fixed budget or time constraint, respectively (Kellerer *et al.*, 2004). Specifically, in our task, we are faced with an online multiple-choice

knapsack problem (MCKP), where we need to make an instant and irrevocable decision when a user arrives. In this study, the optimal discount rate to maximize the purchase conversion rate and profits is adjusted based on a deep neural network.

## 2.4. Behavioral signals and clickstream analysis

The online setting supports the hedonic experience of consumption by removing some of the usual in-store behavioral restraint signals (Dittmar *et al.*, 2004). In particular, research has shown that about 65% of purchases in online stores are made on impulse (Nielsen *et al.*, 2017). It is known that website experience, convenience and “web atmospherics” (including graphics, search engine and one-click purchasing) are likely to promote impulse purchasing beyond that normally seen in a bricks-and-mortar retail setting (Verhagen and Van Dolen, 2011; Childers *et al.*, 2001).

Impulsive purchasing is an act of buying a product with a sudden desire to buy when you see a certain product or advertisement while shopping. Within the online shopping mall platform, the customer's page click stream history is directly related to the preceding sign of impulse purchasing. A representative example of an impulse purchase is the act of continuously clicking on a specific advertisement page or leaving a product-related question on a bulletin board after viewing a product detail page (Ah Fook and McNeill, 2020). The act of continuously viewing product review bulletin board pages is also an action that leads to an impulsive purchase.

On the other hand, non-impulse buyers can be classified as follows (Schade, 2014). Customers with clear purchasing goals already know what they want to buy, so they prefer to shop quickly and are less likely to browse for other products. Therefore, the click stream is very short, and it has a very short path to go directly to the shopping cart after seeing a specific product. The characteristic of customers who carefully plan and purchase is that they visit several shopping malls to collect information before making a purchase decision. In addition, they make decisions by carefully examining product details and buyers' reviews. Therefore, customers who read multiple details or purchase reviews of similar products belong to this type. These types of customers have a relatively clear intention to purchase, and therefore have a high conversion rate.

The following are the characteristics of customers browsing shopping malls with a low conversion rate. Customers who just browse shopping malls are the type to explore new products in order to select products that they may purchase in the future. After checking the product offline in advance, they may explore it again online. In the case of these shoppers, they look around the shopping mall because they may have a need to purchase to some extent in the future. Therefore, they have a lot of interest in the page for new products, popular products, and sale products.

One-time customers are often unfamiliar with the site or the products. This is the type with the lowest conversion rate. They often start with membership registration. In addition, since they are not familiar with the shopping mall website, they click on various pages without any pattern out of curiosity. This study reduces the churn rate by issuing discount coupons to customers with a high risk of churn by analyzing each customer's page click history.

Building upon these prior research streams, the present study focuses on integrating behavioral prediction, recommendation generation, and operational coupon optimization into a unified real-time framework. Rather than treating these components independently, the proposed system emphasizes their interaction within practical e-commerce decision environments.

To strengthen the critical evaluation, we reinterpret the connection between existing methods and our proposed framework as follows:

1. Personalized recommendation and intent detection studies have successfully modeled individual user behavior, yet most of them stop at improving recommendation accuracy. They rarely extend to profit optimization or integrated decision pipelines. Our study advances this by linking behavioral prediction to economic outcomes through real-time coupon allocation.
2. Knapsack-based optimization studies have traditionally focused on static decision problems under limited resource constraints. However, in practical e-commerce environments, coupon allocation decisions must be made sequentially and dynamically as users arrive. The proposed model transforms the static multiple-choice knapsack formulation into a real-time adaptive decision problem, where discount allocation functions as a continuous profit optimization process guided by learned behavioral probabilities. This establishes a clear conceptual bridge between combinatorial optimization theory and operational marketing AI systems.
3. Buying-sign and clickstream analyses in prior literature have emphasized behavioral interpretation but lacked an explicit computational link to pricing and allocation. Our study integrates these behavioral signals directly into a predictive-prescriptive framework, where observed clickstream features drive real-time decision-making on coupon issuance.

By critically synthesizing these streams, this research moves beyond descriptive literature review and positions its contribution at the intersection of behavioral prediction, economic optimization, and real-time decision systems.

## 3. RESEARCH METHODOLOGY

This study proposes a three-stage hybrid framework for real-time coupon issuance that integrates purchase intention estimation, personalized recommendation, and discount optimization. Each stage is designed to handle distinct sub-tasks:

(1) predicting user churn and purchase intent, (2) recommending personalized coupon categories through CF+content-based modeling, and (3) dynamically allocating discount rates to maximize profit.

Although the framework is modularized into three stages for interpretability and operational flexibility, the overall system operates as a synchronized real-time decision pipeline. During online inference, the purchase and stay probabilities estimated in Stage 1 are immediately propagated to the recommendation and discount optimization modules. Furthermore, coupon redemption and purchase outcomes generated after deployment are periodically fed back into the retraining process, enabling adaptive synchronization among all stages.

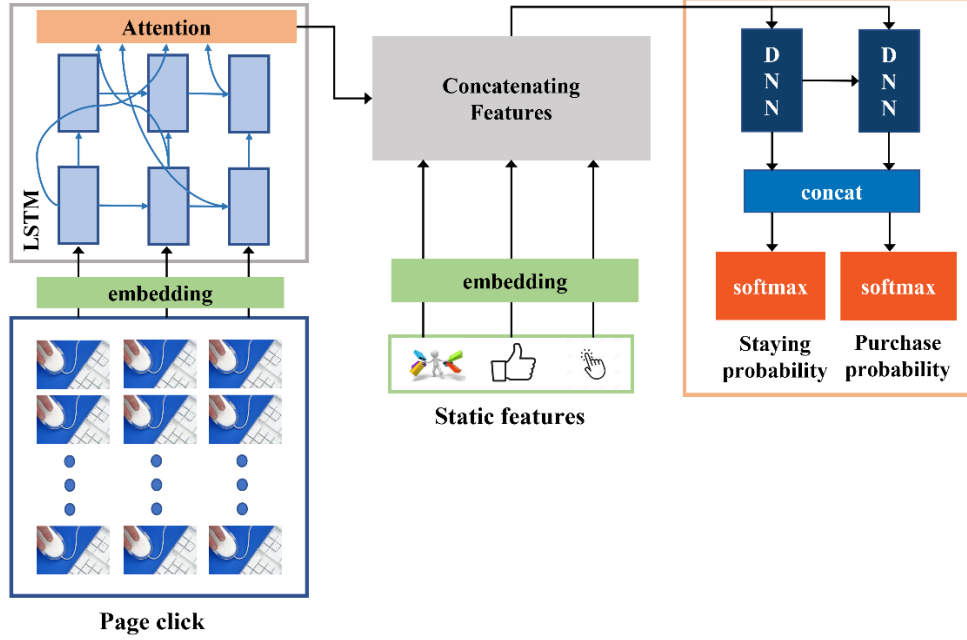


Figure 1. Architecture of the proposed purchase intention model.

As shown in Figure 1, the clickstream sequence is processed through the embedding layer and LSTM hidden-state sequence. The final hidden state serves as the query vector in the attention module, while all hidden states are used as key and value vectors to generate the attention-weighted context vector. The resulting representation is concatenated with static customer features and passed to the DNN layer for joint prediction of stay and purchase probabilities.

### 3.1. Stage 1: User intention detection

The first stage estimates the probability of purchase and probability of stay for each customer session based on real-time clickstream data and static user attributes. The model architecture consists of an embedding layer, an LSTM layer with attention, a concatenation layer, and a DNN output layer (Figure 1).

#### 3.1.1. Embedding layer

The input features are divided into:

- Dynamic features: clickstream events representing page visits, view durations, and navigation order.
- Static features: demographic attributes (age, gender, region) and membership levels.

Each categorical variable is transformed into dense 128-dimensional vectors through a shared embedding matrix. This process ensures heterogeneity alignment between real-time and static data, providing compact numerical inputs for the sequential model.

#### 3.1.2. LSTM layer

The embedded dynamic sequence is processed using an LSTM network to capture temporal user behavior and long-term dependencies. The LSTM computes hidden states  $h_t$  and cell states  $c_t$  at each timestep  $t$ , as follows:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \quad (1a)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \quad (1b)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \quad (1c)$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c), \quad (1d)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \quad (1e)$$

$$h_t = o_t \odot \tanh(c_t), \quad (1f)$$

where  $x_t$  is the embedded feature vector,  $h_t$  the hidden state, and  $c_t$  the cell state. The sequence of hidden vectors  $[h_1, h_2, \dots, h_T]$  serves as the contextual representation of user behavior over time.

### 3.1.3. Attention mechanism

To identify key behavioral patterns, a lightweight attention mechanism is applied on top of the LSTM outputs. Let  $H = [h_1, h_2, \dots, h_t] \in R^{T \times d_h}$  denote the sequence of hidden states generated by the LSTM layer. In this study, the final hidden state  $h_t$  is used as the query vector because it represents the summarized context of the entire session, while all timestep hidden states are used as key and value vectors:  $Q = W_Q h_t$ ,  $K = W_K h_t$ ,  $V = W_V h_t$ . Attention weights and context vector  $c$  are calculated as:

$$\alpha_i = \frac{\exp\left(Q \cdot \frac{K_i}{\sqrt{d_k}}\right)}{\sum_{j=1}^n \exp\left(Q \cdot \frac{K_j}{\sqrt{d_k}}\right)}, \quad (2a)$$

$$c = \sum_{i=1}^n \alpha_i V_i. \quad (2b)$$

This operation highlights crucial user actions (e.g., product detail views or cart additions) while suppressing noise from less relevant interactions. Because  $Q$ ,  $K$ , and  $V$  originate from the LSTM hidden states, the attention efficiently captures dependencies across time without additional computational overhead.

### 3.1.4. Fusion and DNN layer

The attention-weighted context vector  $c$  is concatenated with static user embeddings and passed through a deep feed-forward network (DNN). This DNN performs joint multi-task prediction of both stay and purchase probabilities using two sigmoid outputs:

$$\hat{y}^s = \sigma(W_s + b_s), \quad (3a)$$

$$\hat{y}^p = \sigma(W_p + b_p). \quad (3b)$$

The joint loss is defined as:

$$L = -\frac{1}{N} \sum_{i=1}^N [(y_i^s \ln \hat{y}_i^s + (1 - y_i^s) \ln(1 - \hat{y}_i^s) + y_i^p \ln \hat{y}_i^p + (1 - y_i^p) \ln(1 - \hat{y}_i^p))]. \quad (4)$$

This formulation jointly optimizes both sub-tasks while implicitly addressing class imbalance between purchase and non-purchase cases, without redundant oversampling. The theoretical motivation behind the dual-task formulation is that a purchase event is conditionally dependent on a prior staying behavior within the shopping session. In practical e-commerce environments, users who immediately leave the platform rarely generate purchases, whereas prolonged engagement behavior substantially increases purchase likelihood. By jointly modeling staying probability and purchase probability, the framework captures this conditional dependency structure while alleviating severe purchase-label imbalance.

### 3.1.5. Hyperparameter optimization

Hyperparameters such as learning rate, dropout rate, hidden dimension, and batch size are tuned through Bayesian optimization. Training uses the Adam optimizer with parameters  $\epsilon = 3 \times 10^{-4}$ ,  $\beta_1 = 0.8$ , and  $\beta_2 = 0.999$ . The maximum sequence length is set to 100, with zero-padding for shorter sessions. The  $\beta_1$  parameter is set to 0.8 based on Bayesian hyperparameter optimization rather than being manually predetermined.

### 3.2. Stage 2: Recommendation module

The second stage recommends personalized coupon categories by combining content-based and collaborative filtering (CF) methods.

Content-based filtering analyzes each user's historical click and purchase logs to compute similarity scores between product category embeddings. Cosine similarity or TF-IDF-based metrics are applied to represent user preferences.

Collaborative filtering extracts latent user-item representations using matrix factorization, identifying users with similar behavioral patterns.

Integration: The two recommendation signals are fused as a weighted ensemble:

$$Score(u, i) = \lambda \cdot ScoreCF(u, i) + (1 - \lambda) \cdot ScoreCB(u, i), \quad (5)$$

where  $\lambda$  controls the balance between collaborative and content-based components (initially set to 0.5 and tuned via validation). This integrated strategy mitigates the cold-start and data sparsity issues inherent in conventional CF models while preserving personalization. Validation experiments were conducted using  $\lambda$  values from 0.1 to 0.9 at intervals of 0.1. Purchase conversion rate was used as the validation metric, and  $\lambda=0.6$  produced the best performance and was therefore selected.

### 3.3. Stage 3: Coupon allocation optimization

In the final stage, a deep neural network regression model dynamically determines the optimal discount rate for each user to maximize expected profit, as illustrated in Figure 2.

Given the estimated purchase probability  $P(p | x)$  and candidate discount rates  $d \in \{5\%, 10\%, 15\%\}$ , the model learns to select  $d^*$  that maximizes:

$$\text{Profit}(d) = (1 - d) \times P(p | x, d). \quad (6)$$

The dependent variable is the binary purchase outcome, and independent variables include clickstream features, demographic attributes, and issued discount rates. The model is trained on historical coupon issuance data to learn non-linear relationships between discount sensitivity and purchase behavior. Finally, the selected  $d^*$  is applied to issue a personalized coupon in real time.

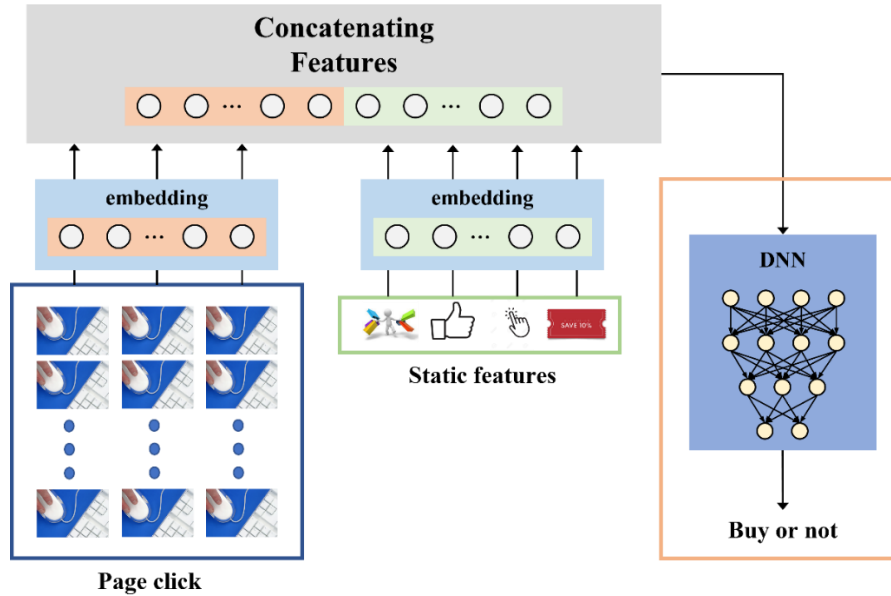


Figure 2. Real-time coupon allocation optimization architecture. Behavioral prediction outputs and recommendation results are integrated into the DNN-based discount optimization module, which dynamically estimates the expected operational profit score for candidate discount rates and issues personalized coupons in real time.

### 3.4. Summary of framework

Table 2 summarizes the modular structure of the proposed framework, describing the objective, model type, input features, and output of each stage. This modular design clarifies the hybrid nature of the proposed system and highlights

how time-series prediction, recommendation, and profit optimization interact within a unified framework for intelligent coupon issuance.

Table 2. Summary of the Framework

| Stage                       | Objective                                | Model Type       | Key Input Features                        | Output                      |
|-----------------------------|------------------------------------------|------------------|-------------------------------------------|-----------------------------|
| 1. User Intention Detection | Estimate churn and purchase intent       | LSTM + Attention | Real-time clickstream + static attributes | Stay & purchase probability |
| 2. Recommendation           | Recommend personalized coupon categories | CF + CB          | User log & category vectors               | Top-k product categories    |
| 3. Coupon Allocation        | Optimize discount for maximum profit     | DNN regression   | Purchase probability & discount rates     | Optimal discount ( $d^*$ )  |

## 4. EXPERIMENTAL RESULTS

### 4.1. Dataset

This study experimented with a women's underwear shopping mall. The shopping mall is a low-cost women's shopping mall targeting women in their teens and twenties. Many young women visit through active SNS marketing pages where beautiful young models take pictures with the shopping mall's products. The main users are students, so they are very sensitive to price and their own tastes. In addition, since it sells all categories of women's underwear, we judged that it is suitable for this study. Through a contract with the writer's running company, we received permission to track all logs and member information data of the shopping mall and were able to research coupon issuance.

Our data set contains user sessions from the website of an online shop and was collected in the period from Feb 13th, 2022 to June 12th, 2023. The mall sells a total of 421 products consisting of more than 10 categories. Average daily sales are about 1,600\$ (2 million KRW), average daily visitors (including members and non-members) are about 11,302, and average daily page views are about 7,000 pages. Visitors who enter the website and immediately leave without clicking anything have a page click count of 0. We utilized JavaScript code on each shopping mall web page to store log data in real-time. Stored logs include page click history, purchase history, shopping cart history, order history, search history, etc.

### 4.2. Experimental design

To ensure methodological rigor and reproducibility, all experiments in this study followed a standardized design framework consisting of four components: objective definition, dataset specification, experimental procedure, and evaluation metrics.

**Objective definition:** The primary objective was to validate the effectiveness of the proposed three-stage hybridized framework in improving both purchase intention prediction accuracy and profit optimization through coupon allocation.

**Dataset specification:** All data were collected from a live e-commerce platform between February 2022 and June 2023, comprising 6,985,005 user sessions. The data include page clickstreams, purchase logs, and demographic information.

#### Experimental procedure:

Step 1: Model training for purchase intention prediction using the proposed LSTM + Attention architecture.

Step 2: Coupon recommendation using CF + content-based filtering.

Step 3: Profit evaluation via DNN-based discount optimization at 5%, 10%, 15%, and dynamic rates. Statistical testing was conducted using independent two-sample t-tests at a 5% significance level.

Because users were randomly divided into mutually independent experimental groups, independent two-sample statistical testing was more appropriate than paired statistical analysis.

**Evaluation metrics:** For classification (purchase intent), AUC, confidence intervals, and learning time were used. For coupon issuance and profit experiments, conversion rate improvement and relative profit indices were evaluated. Each result was reported with 95% confidence intervals to ensure statistical transparency.

### 4.3. Identifying purchase intention

In this study, purchase intention is estimated using the Area Under the ROC Curve (AUC). AUC measures the pairwise ranking performance of the classification results. The methodology proposed in this study was compared with other methods as shown in Table 3. First, purchase intention was estimated using the simplest regression analysis and Gradient

Boosting using only dynamic clickstream variables. Also, clickstream variables were used, but RNN and DNN, which are basic deep learning techniques for time series variable estimation, were combined.

In the proposed methodology, attention was removed from the LSTM layer to estimate the importance of the attention mechanism. We also estimated it by removing static variables from the proposed methodology. Through this, we confirmed the significant impact that static meta variables have on real-time clickstream data analysis. Lastly, we removed the staying probability from the proposed methodology. In conclusion, the proposed methodology had the highest accuracy in estimating purchase intention, and other methodologies that eliminated some mechanisms from the proposed methodology had lower accuracy than the proposed methodology. The method that showed the most similar performance to the proposed methodology was a methodology that removed static variables, and there was some overlap in the confidence interval with the proposed methodology. The ablation experiments demonstrate that each architectural component contributes meaningfully to predictive performance. In particular, the removal of the attention mechanism reduced the model's ability to capture temporally important behavioral interactions, while excluding static customer features weakened user-context representation.

Furthermore, eliminating the staying-probability task significantly degraded robustness against extreme purchase-label imbalance, supporting the theoretical importance of the proposed conditional dual-task formulation. Additionally, there was no significant difference in learning time compared to other methodologies. Because model training can be performed in batches during off-peak hours, the proposed framework can be deployed on real-world e-commerce platforms. For this experiment, a total of 6,985,005 session data were collected and studied over a period of one year, and the experiment was conducted with log data of 535,836 sessions visited during one month in January 2024. All were significant at the 5% significance level.

Table 3. The results of the purchase intention experiment

| Method                                                 | AUC   | Confidence intervals | Learning time (The proposed methodology is set at 100) |
|--------------------------------------------------------|-------|----------------------|--------------------------------------------------------|
| Logistic regression with click stream                  | 0.623 | 0.598~0.648          | 82.71                                                  |
| Gradient Boosting with click stream                    | 0.673 | 0.653~0.693          | 90.36                                                  |
| RNN+DNN with click stream                              | 0.685 | 0.658~0.712          | 93.16                                                  |
| Proposed method without attention                      | 0.720 | 0.693~0.747          | 93.23                                                  |
| Proposed method without static feature                 | 0.732 | 0.702~0.762          | 99.35                                                  |
| Proposed method without predicting staying probability | 0.715 | 0.69~0.74            | 97.28                                                  |
| Proposed method                                        | 0.747 | 0.723~0.771          | 100                                                    |

#### 4.4. Issuance of coupons based on purchasing preferences

The effect of issuing personalized coupons was measured based on the purchase conversion rate of whether purchases were made using the issued coupons. Clickstream, shopping cart, and purchase history were used as learning variables for the recommendation system. We issued coupons to users that have under 30% purchase intention probability with our proposed method. Also, we randomly split users into six groups and issued coupons to one group with a random category and the others with the above methods to compare purchase conversion rate with the random method. And we calculated the improvement rate of the purchase conversion rate between the two groups. Compared to issuing coupons randomly, the purchase conversion rate increased significantly when coupons were issued using a recommendation system algorithm. Even when coupons for best-selling category products were simply issued, the purchase conversion rate increased by 20.43% compared to when coupons were issued randomly, showing a clear increase. However, simply having a lot of conversions to best-selling category products is not good from a shopping mall's profit perspective. Because this group sells well even without issuing coupons, issuing a discount coupon may actually lower the rate of return. When coupons for new product groups were issued, the increase in conversion rate was somewhat small. However, when the CF model and content-based model were applied, the increase increased significantly. In particular, unlike the content-based model, the CF model recommends products that are different from the product the user was previously interested in, but the growth rate was similar to that of best-selling products. The integrated CF+content-based recommendation strategy achieved the highest conversion improvement among all evaluated recommendation approaches.

Table 4 shows the purchase conversion rate improvement rate and confidence interval within the significance level of 5% according to each experimental method. For this experiment, a total of 6,985,005 session data were collected over one year to learn the recommendation system, and each method was tested for one month in February 2024. Tests were conducted on 395,842 sessions randomly divided into six methodologies.

Table 4. The results of the coupon issuance from a recommendation method perspective

| Method                                                    | Improvement rate of purchase conversion rate | confidence intervals |
|-----------------------------------------------------------|----------------------------------------------|----------------------|
| Issued by best-selling category                           | 20.43%                                       | 19.13%~21.73%        |
| Issued by new category                                    | 5.23%                                        | 4.93%~5.53%          |
| Issued by CF model                                        | 19.71%                                       | 17.31%~22.11%        |
| Issued by content-based model                             | 28.43%                                       | 25.53%~31.33%        |
| Issued by proposed CF+content-based recommendation system | 32.65%                                       | 28.45%~36.85%        |

Table 5. The results of the coupon issuance from a profit point perspective

| Discount rate          | Coupon issuance rate                                    | Improvement ratio of purchase conversion rate              | Sales amount after coupon issuance |
|------------------------|---------------------------------------------------------|------------------------------------------------------------|------------------------------------|
| 5%                     | 5.25% (5.05%~5.45% with 95% confidence interval)        | 32.43% (31.03%~33.83% with 95% confidence interval)        | 101.3549                           |
| 10%                    | 5.43% (5.2%~5.66% with 95% confidence interval)         | 45.72% (42.62%~48.82% with 95% confidence interval)        | 101.6913                           |
| 15%                    | 4.97% (4.84%~5.1% with 95% confidence interval)         | 65.46% (60.16%~70.76% with 95% confidence interval)        | 102.0199                           |
| <b>Proposed method</b> | <b>5.32%</b> (4.99%~5.65% with 95% confidence interval) | <b>57.61%</b> (54.21%~61.01% with 95% confidence interval) | <b>103.1549</b>                    |

#### 4.5. Statistical Validation and Robustness Analysis

To verify the statistical significance of the experimental results, t-tests were conducted between the proposed model and all baseline methods listed in Table 3 and Table 4.

For both the purchase intention estimation and the coupon issuance experiments, the null hypothesis ( $H_0$ ) assumes that there is no difference in mean performance between models. The t-tests were performed at a 5% significance level ( $\alpha = 0.05$ ).

Results showed that all comparisons between the proposed model and baseline models yielded p-values  $< 0.05$ , confirming that the observed improvements are statistically significant.

In addition, to ensure the robustness and reliability of the proposed model, the following analyses were performed:

1. Cross-validation robustness: Each experiment was repeated five times with different random seeds and user-session partitions. The standard deviations of AUC and improvement rates were below 0.01, indicating consistent model performance across folds.
2. Noise injection test: To simulate potential sources of experimental error such as inconsistent clickstream logs or partial data loss, Gaussian noise (mean = 0,  $\sigma = 0.05$ ) was added to 10% of the test samples. The model's AUC decreased by less than 1.2%, demonstrating resilience to minor input perturbations.
3. Data imbalance and sampling variation: Random undersampling and oversampling tests confirmed that the model maintained stable performance under varying class ratios, validating its robustness against imbalance-driven bias.

These statistical and robustness validations demonstrate that the proposed framework not only achieves high performance but also maintains statistical reliability and experimental stability across varying conditions. The wider confidence interval observed for the proposed recommendation framework reflects increased personalization variability resulting from the integration of collaborative filtering and content-based recommendation signals. Despite the increased variance, performance improvements remained statistically significant across all experimental repetitions.

#### 4.6. Profit Measurement based on Discount Rate Adjustment

Coupons were issued at 5%, 10%, 15%, and an adjusted rate according to the method proposed in Subsection 3.3. When conducting experiments for each discount rate application method, the purchase intention estimation and coupon product group recommendation methods followed the proposed methods. We randomly split users into four groups and issued coupons with each method to compare profits. We estimated how much actual sales would be increased by issuing coupons. Sales amount without coupon issuance was assumed to be 100, and sales after coupon issuance were estimated using the ratio of coupon issuance customers and the discount rate. The specific calculation method is as follows:

$$\text{Sales amount after coupon issuance} = 100 * \text{coupon issuance ratio among all customers} * (1 + \text{improvement ratio of purchase conversion rate}) * (1 - \text{discount rate}) + 100 * \text{ratio of customers not given coupons}.$$

As a result of the experiment, as shown in Table 5, there was a big difference in the rate of return depending on how the same discount rate was applied. Rather than uniformly sticking to a specific discount rate, returns were maximized when the discount rate was adjusted in real time to optimize profits depending on the situation. When a 5% discount coupon was simply issued, the rate of return improved by about 1.35% compared to before issuing the coupon, but when the discount rate of 5% to 15% was dynamically adjusted, the rate of return improved by about 3.15% compared to before the coupon was issued.

For this experiment, each methodology was tested for one month in March 2024. Tests were conducted on 425,441 sessions randomly divided into four methodologies.

The current experimental design employed discrete discount levels of 5%, 10%, and 15% to facilitate controlled comparisons and ensure operational interpretability. Nevertheless, the proposed deep learning-based optimization framework can be readily extended to determine discount rates on a continuous scale, enabling more flexible and fine-grained discount allocation. In real-world deployment, the DNN regression model introduced in Stage 3 can be adapted to output a continuous-valued optimal discount  $d^* \in [0, 0.3]$ , rather than selecting among predefined rates. Preliminary internal simulations suggest that such continuous modeling can capture finer-grained sensitivity between purchase probability and margin trade-offs, allowing for smoother profit optimization across diverse customer segments. However, this requires dynamic pricing control and stakeholder approval within live e-commerce operations, which will be explored in future extensions of this study. The proposed framework was deployed using periodic batch retraining during low-traffic nighttime intervals, while real-time inference was performed online with lightweight neural architectures to minimize operational latency. In practical deployment environments, the average end-to-end inference latency remained sufficiently low for real-time coupon issuance.

#### 4.7. Discussion

The experimental results demonstrate that the proposed framework effectively integrates behavioral prediction, recommendation generation, and economic optimization within a unified real-time operational pipeline. Unlike prior studies primarily focusing on recommendation accuracy or churn prediction independently, this study emphasizes the interaction among sequential behavioral modeling, personalized recommendation, and profit-aware decision-making. The ablation experiments indicate that the attention mechanism, static feature fusion, and conditional dual-task formulation each contribute meaningfully to predictive performance improvement. In particular, jointly estimating staying probability and purchase probability appears effective for alleviating severe purchase-label imbalance commonly observed in real-world e-commerce environments. Compared with prior recommendation-focused studies, the proposed framework additionally incorporates operational constraints including real-time inference, coupon allocation timing, and profit optimization. These findings suggest that practical industrial deployment requires balancing predictive performance with computational efficiency and deployment stability.

Nevertheless, several limitations remain. First, the framework was validated on a single operational shopping mall dataset targeting a relatively narrow customer demographic. Second, transformer-based sequential architectures such as SASRec and BERT4Rec were not empirically benchmarked under identical deployment conditions. Future research should therefore investigate cross-domain validation, transformer-based benchmarking, uplift modeling, and reinforcement-learning-based dynamic pricing optimization under real-time operational constraints.

## 5. CONCLUSIONS

In this paper, we solved the problem of digital coupon allocation using a time series deep learning model. To overcome the data label imbalance problem, the probability of staying and the probability of purchase are estimated together to estimate customer churn probability. In addition, real-time page click time series data and static customer meta information were used together. For customers with a high risk of churn, coupons of recommended categories were issued using a CF+content-based recommendation system, and coupons with the optimal discount rate were issued for each customer to optimize shopping mall profits. Extensive experiments show the superiority of our proposed framework on the coupon allocation task.

### 5.1. Implications

This study contributes by demonstrating a cross-domain integration framework that unites time-series behavioral modeling, recommendation modeling, and economic optimization within a single deep learning architecture. First, unlike prior studies that focus on one-dimensional recommendation accuracy, our framework extends methodological novelty through multi-objective learning — simultaneously optimizing user-level behavioral prediction and profit maximization.

Second, this work introduces a conditional dual-probability design (stay + purchase) to alleviate extreme label imbalance, which has not been addressed in previous LSTM+Attention-based intent models. Third, because the system primarily operates on behavioral logs and anonymized identifiers, it can reduce reliance on directly identifiable customer information. However, clickstream data may still be considered personal data under applicable privacy regulations such as GDPR, PDPA, and PIPA. Therefore, appropriate anonymization, governance, and regulatory compliance procedures remain necessary. Thus, the contribution is not limited to a mechanical combination of standard modules but to a novel hybrid orchestration enabling robust real-time marketing decision-making.

## 5.2. Limitations and future research

Our research has some limitations that open up opportunities for future research. First, experimenting with more combinations of model parameters will lead to clearer results. For this, the consent of the stakeholders in the shopping mall is needed.

Second, in this study, coupon discount rates were limited to three discrete values (5%, 10%, and 15%) for experimental clarity and practical implementation constraints. However, in real-world business environments, the optimal discount is often continuous rather than discrete. Future research will therefore extend the current deep learning-based profit optimization model to a continuous regression framework, capable of dynamically adjusting discount rates in real time. This approach can leverage reinforcement learning or differentiable optimization to find fine-grained discount levels that maximize profit while maintaining user fairness and budget constraints.

Third, machine learning is an active field of research, and new modeling approaches keep appearing. For example, it might be worth considering a convolutional layer to train a better feature representation before processing the sessions through recurrent layers. Although CNNs are widely used in the computer vision field, they can also be applied to shopping mall data analysis to learn spatiotemporal properties.

Fourth, this study is a coupon issuance study based on clickstream real-time data. Through this, real-time churn risk is estimated, and coupons are issued to customers with a high churn probability. Therefore, real-time data collection is essential. However, most shopping malls do not know how to collect data technically. In the future, research is needed to specifically propose real-time data collection methodologies.

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