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# Analysis of Consumer Behavior Pattern Changes and Preferences on Cross border E-commerce Platforms Driven by the Digital Economy

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**SUMMARY:** *Driven by the digital economy, personalized recommendation methods are studied to address the problem of information overload in response to changes in user behavior patterns and preference analysis needs on cross-border e-commerce platforms, which can help improve user shopping efficiency and satisfaction. This article proposes a Deep Incremental Recommendation (DIR) model, which is co trained with the basic model and incremental model. By utilizing the prediction error of consumer behavior preference historical data and the sorting error of incremental data on e-commerce platforms to optimize parameters, combined with Dynamic Convolution, the HGNetV2 backbone network is improved to enhance feature extraction ability and model generalization. The experiment was based on a publicly available dataset on Taobao, and compared with benchmark models such as BPR, CF, and CFN. The experimental results showed that the proposed method improved accuracy by 35.5% (0.2387-0.2439) when the number of users increased from 10 to 60, with a stable recall rate of over 15% and an F1 score of 0.1854 (61.5% higher than CFN); When the number of recommended products K=10, the accuracy, recall, and F1 value all reach their peak values, and the curve is smooth with high convergence efficiency. Research has shown that the proposed model effectively balances precise recommendation and interest coverage through dynamic preference weight allocation and multi-scale feature fusion, significantly improving the personalized recommendation performance of cross-border e-commerce platforms.*

***KEYWORDS:*** *digital economy; Cross border e-commerce platforms; Changes in behavioral patterns; Consumer preferences; Personalized recommendation; Dynamic Convolution*

## 1 Introduction

With the rapid growth of information and the development of technology, everyone's lifestyle has undergone earth shattering changes. Traditional offline businesses rely on the Internet and mobile e-commerce platform, which can effectively and quickly complete the original complex and lengthy business [1]. At the same time, emerging businesses also rely more on the development of Internet e-commerce platforms, such as e-commerce, online video, social networks, mobile news, etc. E-commerce platforms represented by Alibaba, JD.com, Amazon, etc. enable people to purchase goods from all over the world at home, and the rapid development of mobile platforms has made mobile e-commerce a guarantee for users to shop and transact anytime, anywhere. Online long video websites represented by iQIYI, Mango TV, Tencent Video, etc. also derive other businesses with the development of the Internet and mobile platforms. Short video apps such as Kwai and Tiktok have occupied the leisure time of most

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users with their excellent recommendation algorithms [2]. Mobile news services such as Today's Headlines have gradually replaced traditional media such as newspapers.

The transformation of business models has brought convenience to people's lifestyles, but it has also led to explosive growth of business data. Although these data can provide rich and colorful information, they also bring serious information overload problems [3, 4]. Obtaining information is an effective way for humans to understand and comprehend the world. Only by obtaining valuable information for users can we truly achieve understanding and comprehension. However, the current world is a world of thousands of people, and everyone needs unique information [5]. If we divide it into two parts, on the one hand, from the user's perspective, the ubiquitous information brings them a dull and boring experience, and personalized push notifications from e-commerce platforms can arouse users' interest; On the other hand, from the perspective of enterprises, it is extremely important to improve user retention and stickiness among users through high-quality personalized content distribution mechanisms on e-commerce platforms, after attracting new users through advertising purchases and other means. These demands also indicate the importance of information recommendation on e-commerce platforms for human life, and we are moving from the information age to the recommendation age [6]. As an important product in the field of artificial intelligence, the preference recommendation system for consumer behavior patterns on e-commerce platforms has become a necessary tool to solve the problem of information overload, and has been widely accepted and applied in various industries. From the thousands of people and faces on Taobao pages to the personalized content integration of Today's Headlines e-commerce platforms, personalized recommendations on e-commerce platforms provide users with convenient personalized decision support and information services, and also provide a way for e-commerce platform enterprises to achieve data landing and digital innovation [7].

The e-commerce platform's consumer behavior preference recommendation system aims to help users discover potential services and information they need in a vast amount of information. Unlike information retrieval systems represented by search engines that only provide information to users based on keywords, e-commerce platform consumer behavior pattern preference recommendation systems effectively mine users by mining the inherent relationships between user historical behavior information, content information, and other data. The importance of the recommendation system for consumer behavior patterns on e-commerce platforms is self-evident. Therefore, research on personalized recommendation methods for e-commerce platforms is not only of industrial significance, but also of scientific research significance.

# 2 Related research

## 2.1 Research status

At present, the personalized recommendation algorithms for e-commerce platforms that have been researched and promoted in practical scenarios include the following: CF based personalized recommendation algorithm for e-commerce platforms, CB based personalized recommendation algorithm for e-commerce platforms, and a new model of personalized recommendation algorithm for e-commerce platforms that combines DL. The following mainly discusses and introduces excellent recommendation algorithms and characteristics in these directions [8].

(1) Content based recommendation algorithm. The research approach of CB based recommendation algorithm is completely different from CF based recommendation algorithm. It focuses on the characteristics carried by the research object itself, and describes and solidifies

the features of the research object. Abandoning the calculation of similarity between users and products, the main method of CB based recommendation algorithm is to extract the characteristic attributes of users or products, and then use the attributes to find users or products with that attribute, thereby achieving recommendations that meet the characteristics of users and products [9]. The representative design idea is to extract the corresponding keyword vectors of the product from the original dataset using algorithms such as Word2vec, in order to effectively complete the comprehensive analysis and clustering of product keywords. Alternatively, traditional Tf-Iff methods can be used to discover key keywords for users or products, in order to find products that meet user interests based on the attributes represented by the keywords.

(2) Recommendation algorithm based on collaborative filtering. The personalized algorithm for e-commerce platforms based on CF mainly includes UserCF and ItemCF. Among them, ItemCF was first proposed by Amazon in 1988 and successfully applied to the Amazon shopping center website [10]. After this, Netflix, Youtube, Douban and other websites have attempted to use ItemCF for personalized product recommendations on e-commerce platforms for users. [11] The proposed PMF model effectively decomposes the matrix using its unique probability distribution information. At the same time, after decomposing the latent vectors of users and items, auxiliary information is added to improve the model performance. [12] Propose a user video graph model for YouTube video website, establish paths between users and their interested videos, and filter out paths with high similarity nodes. In addition, in recent years, many scholars have conducted research on collaborative filtering e-commerce platform consumer behavior pattern preference recommendation systems based on graph models and achieved certain results.

(3) Recommendation algorithm based on deep learning. In recent years, research on deep learning has been widely applied and implemented internationally, mainly in the fields of computer vision and natural language processing, where it has developed rapidly and achieved great technological breakthroughs. The main deep learning models used are as follows: common models such as DNN, CNN, and RNN. [13] Considering that recommendation models lack a certain degree of generalization ability while possessing memory capabilities, resulting in falling into local optimal recommendations. So adding a DNN model on top of the LR model helps users find more diverse and imaginative products. [14] The proposed DeepFM model and the Deep&Cross model proposed in [15] construct parallel structures including width modules and depth modules, which can extract low - and high-order features and improve the accuracy of click through rate estimation in e-commerce platform consumer behavior pattern preference recommendation systems. Recurrent neural networks have also been applied in consumer behavior pattern preference recommendation systems for e-commerce platforms. [16] When engaged in news recommendation work, it was also found that news information has good temporal characteristics. Therefore, a recurrent neural network was introduced into the model to help predict news hotspots.

## 2.2 Difficult challenges

The preference recommendation system for consumer behavior patterns on e-commerce platforms has unique characteristics and difficulties, which are described as follows:

(1) The data in the recommendation system for consumer behavior patterns on e-commerce platforms is extremely sparse. With the development of the times, the number of online content enterprises has sharply increased, and correspondingly, a huge amount of related information is generated every day [17]. However, only some products and information will be discovered and used. It is difficult for e-commerce platform consumer behavior preference

recommendation systems to determine whether a product is loved by users based solely on limited information.

(2) There are compatibility issues between the accuracy and information diversity of personalized recommendation information systems on e-commerce platforms. The personalized recommendation system for consumer behavior patterns on e-commerce platforms often cannot simultaneously balance the two basic attributes of accuracy and diversity of information in personalized recommendation content on e-commerce platforms [18]. Over time, the user experience gradually deteriorates. If the recommendation range is increased, there will be a large number of ineffective product recommendations that deviate from user interests. Therefore, a core task of the recommendation system for consumer behavior patterns on e-commerce platforms is to comprehensively consider accuracy and diversity.

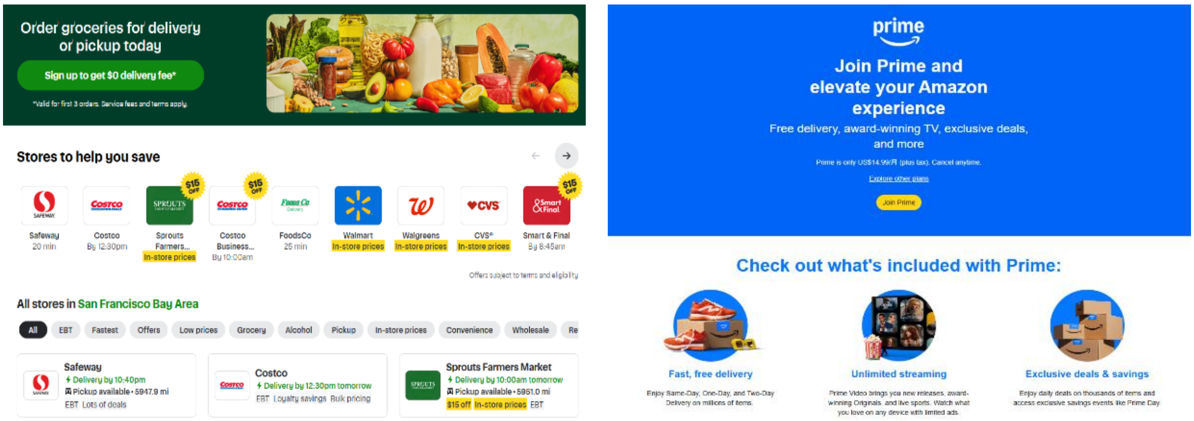
(3) There is a cold start issue in the recommendation system for consumer behavior patterns on e-commerce platforms. In the context of consumer behavior preference recommendation systems on e-commerce platforms, the development of related enterprises cannot be separated from the growth of users. However, with the emergence of new users, there has also been a problem of completely blank information for new users. This will lead to the collapse and failure of the consumer behavior preference recommendation system on e-commerce platforms, resulting in the disorder of recommendation functions, reducing recommendation effectiveness and enterprise efficiency [19].

In the current era of big data with the rapid development of the Internet, enterprises need to combine users' consumption thinking and methods in the development process to design services or products that meet users' needs. And users also need an auxiliary function that can help them make choices when using products or consuming online content. At the same time, user behavior and preferences may have a certain degree of variability over time. Therefore, by combining user contextual information and their basic behavioral patterns, an e-commerce platform consumer behavior pattern preference recommendation system that conforms to user actual behavior can be further designed.

# 3 Cross border e-commerce user behavior preference recommendation

## 3.1 Research scenarios

This article focuses on the recommendation problem of consumer behavior preferences on e-commerce platforms, browsing products, placing orders, and enjoying fast delivery services through applications. Common e-commerce platforms include Hema Fresh, Instacart, and Sam's Club [20]. Take Instacart, an American Internet retail company, as an example (as shown in Figure 1). Users buy food and daily necessities from local supermarkets through their websites or applications, and then the store delivery clerk delivers the goods to the user's door within the specified time.




(a) Instacart platform (b) Amazon platform

*Figure 1: Example of E-commerce Platform*

In the retail industry, the recommendation system for consumer behavior patterns on e-commerce platforms plays a crucial role in helping users find the desired products in a large inventory of goods. Whether in the fields of fashion, e-commerce, or grocery shopping, consumer behavior preference recommendation systems on e-commerce platforms are widely adopted to enhance user experience. Especially in the field of consumer behavior preferences, the application of e-commerce platform consumer behavior pattern preference recommendation systems is crucial for improving user shopping efficiency and satisfaction. Consumer behavior preference recommendation can be based on similar recommendations, combination recommendations, etc., enabling users to quickly find daily necessities that are frequently purchased through e-commerce platform consumer behavior pattern preference recommendation systems, improving shopping efficiency and satisfaction [21].

## 3.2 Research model

The problem to be solved in this article is to recommend products to users based on their known behavioral preferences (such as purchase history), in order to meet the personalized needs of e-commerce platforms. Regard the products purchased by users simultaneously as a shopping basket, and further learn the relationships between products and user preferences [22, 23]. The specific definition of consumer user behavior preference recommendation problem is, assuming there are m users and n products in total. The user set is $U=\{u_1,u_2,\cdots,u_m\}$, the product set is $I=\{i_1,i_2,\cdots,i_n\}$, and $\mathrm{B}_u^T$ is the collection of products in the user's shopping cart at time T. The task of recommending consumer user behavior preferences is given $(u,\mathrm{B}_u^T)$, combined with user historical interaction data, based on recommendation methods to predict user ratings of products, and select Top N products as the user's recommendation list. The specific algorithm process is shown in Figure 2.

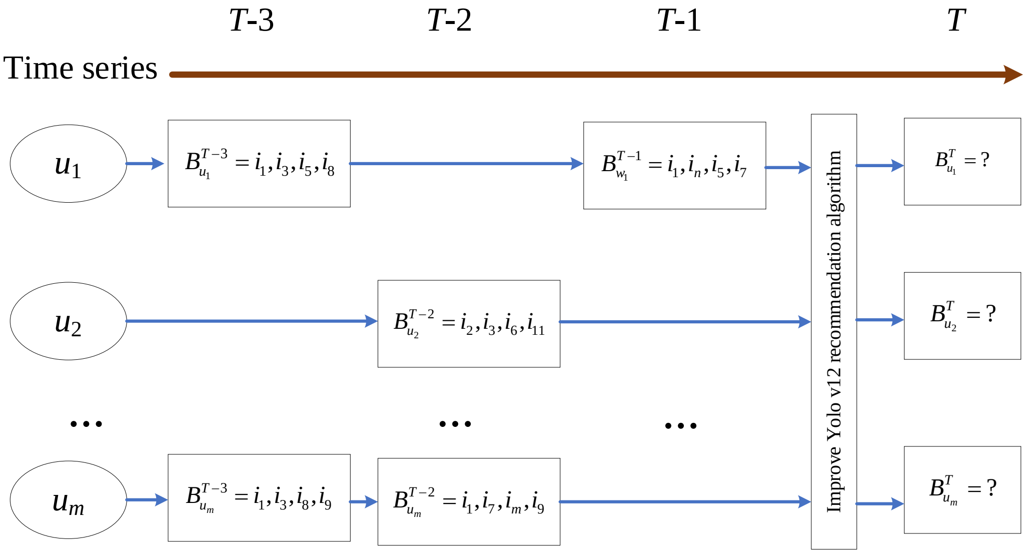



*Figure 2: Schematic diagram of consumer user behavior preference recommendation*

## 3.3 Incremental model recommendation

The incremental process involves two important strategies. For each user, use the trained base model to predict their outstanding historical data during the training process (Figure 3), and use the base model to predict the labeled incremental dataset [24]. Then, these two additional pieces of information are used to learn an incremental model with a smaller number of parameters in incremental training. The base model provides additional information, so the incremental model inherits the sorting ability of the base model.

We calculated the correlation score of the basic model $M_B$ for predicting representative historical data of consumer behavior preferences. The representative historical data of consumer behavior preferences were taken from the part with the smallest prediction error of the basic model. Then, we obtained the top-K item ranking sequence $\pi_{1,\cdots,K}=(\pi_1,\cdots,\pi_K)$, where $\pi_r$ is the item ranked r-th in the sequence. Then, we train a smaller sorting model $M_I$ to minimize the sorting error, distillation error, and performance of the base model on the incremental dataset, which is called data transferability. The loss function we ultimately want to minimize is as follows [25]:

$$\mathcal{L}(\theta_S)=(1-\alpha-\beta)\mathcal{L}^R(\boldsymbol{y},\tilde{\boldsymbol{y}})+\alpha\mathcal{L}^D(\pi_{1\ldots K},\tilde{\boldsymbol{y}})+\beta\mathcal{L}^C(\boldsymbol{y}_{new},\hat{\boldsymbol{y}}) \tag{1}$$

where, $y$ is the true label, $\hat{y}$ is the predicted result of the base model, and $\tilde{y}$ is the predicted result of the incremental model. $\mathcal{L}^R$ is the sorting objective function. Distillation error $\mathcal{L}^D$, using the prediction results of unlabeled items from the basic model to guide incremental model training. $\mathcal{L}^C$ stands for Data Migration Degree, which characterizes the difference between raw data and incremental data. α and β are hyperparameters used to balance three types of errors.

Distillation error can be expressed as [26]:

$$\mathcal{L}^D(\pi_{1,\cdots,K},\tilde{\boldsymbol{y}})=-\sum_{r=1}^{K}\omega_r\log\left(P\left(rel=1\middle|\hat{\boldsymbol{y}}_{\pi_r}\right)\right) \tag{2}$$

where, $\omega_r$ is the importance of the item ranked r-th in the sorted list. There are many ways to measure the importance $\omega_r$ here, such as $\omega_r:\omega_r=1/r$ placing more focus on items that rank higher, and $\omega_r : \omega_r = 1/K$ believing that the weights of each position in the sorting sequence are consistent. $\omega_r : \omega_r = \rho(1-\rho)^r$ believes that the position weights in the sorting sequence satisfy a geometric distribution.

Based on the above, we propose a parameterized geometric weight calculation method [27].

$$\omega_r = e^{-r/\lambda} \quad \text{and} \quad \lambda \in \mathbb{R}^+ \tag{3}$$

where, $\lambda$ is a hyperparameter used to control the sharpness of the distribution, which is obtained through statistical analysis of historical data on consumer behavior preferences. When the hyperparameter is particularly small, the weight calculation method places more emphasis on the top positions in the sequence. When the hyperparameter is large enough, the distribution changes to a uniform distribution.

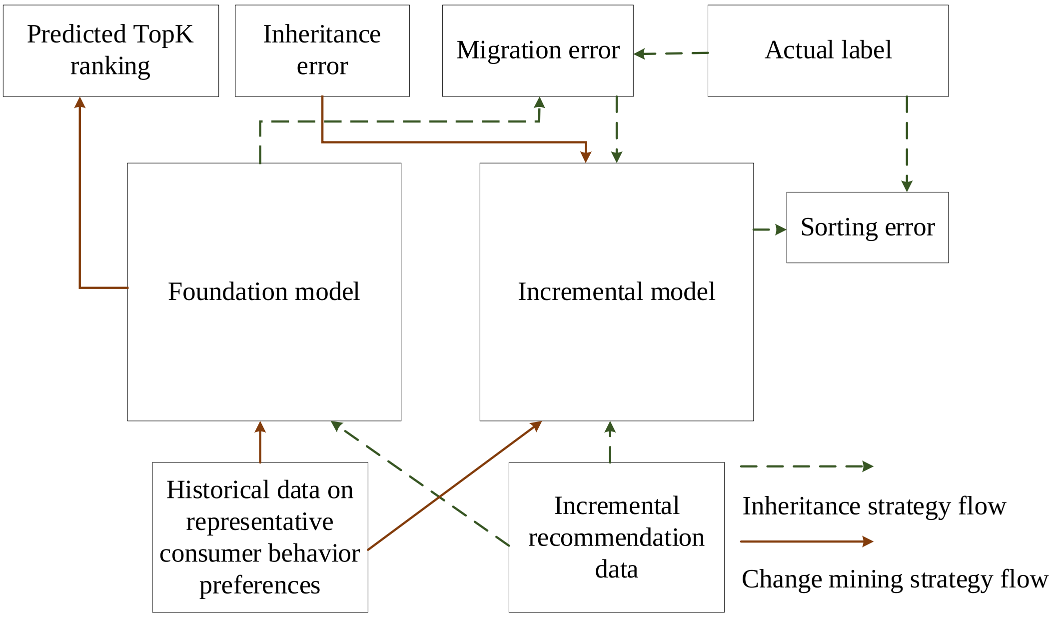



*Figure 3: Depth Incremental Recommendation Model*

The proposed DIR model enables the basic model to teach the incremental model to find correlations and capture their patterns, making the incremental model more versatile and performing well on unknown new data in the future. We use the top K sequences in the predicted results of the base model, rather than the entire sorted list, because noise at lower positions often leads to overfitting of the incremental model to the base model and loss of generality and generalization. In addition, in the sorting problem, only the items ranked high in importance. K is a hyperparameter that represents the level of trust in the underlying model during the teaching process [28]. In addition, over time, there may be significant changes in both the quantity and intrinsic nature of consumer behavior preference historical data and current new data. Therefore, in order to obtain the knowledge that should be obtained from the basic model more accurately, we cannot absorb all the prediction results of the basic model indiscriminately. Unlike the emphasis on historical data of consumer behavior preferences, the performance of the basic model on new data demonstrates the areas where the basic model is powerless against changes in the inherent nature of the data. The basic model can also provide great help for parts that perform poorly in new data, because just as model training requires continuous calculation of errors and iterative updates, our incremental model can truly achieve sufficient generalization [29].

# 4 Improve the Yolo v12 e-commerce user behavior preference recommendation algorithm

## 4.1 Yolo v12 algorithm

YOLO v12 has been optimized based on previous versions, improving computational efficiency with the same detection accuracy and demonstrating superior performance in complex tasks. The YOLO v12 model structure is shown in Figure 4, mainly composed of three parts: backbone network, neck network, and head network, each of which incorporates innovative designs to enhance overall performance. The backbone network is responsible for extracting multi-scale features from input images. The introduced improvement module C3k2 optimizes the feature extraction process by combining repeated convolution with efficient information flow, enhancing feature representation capability while effectively reducing computational burden. In addition, the newly added innovative module C2PSA can effectively filter irrelevant information and enhance detection capabilities in complex scenarios.

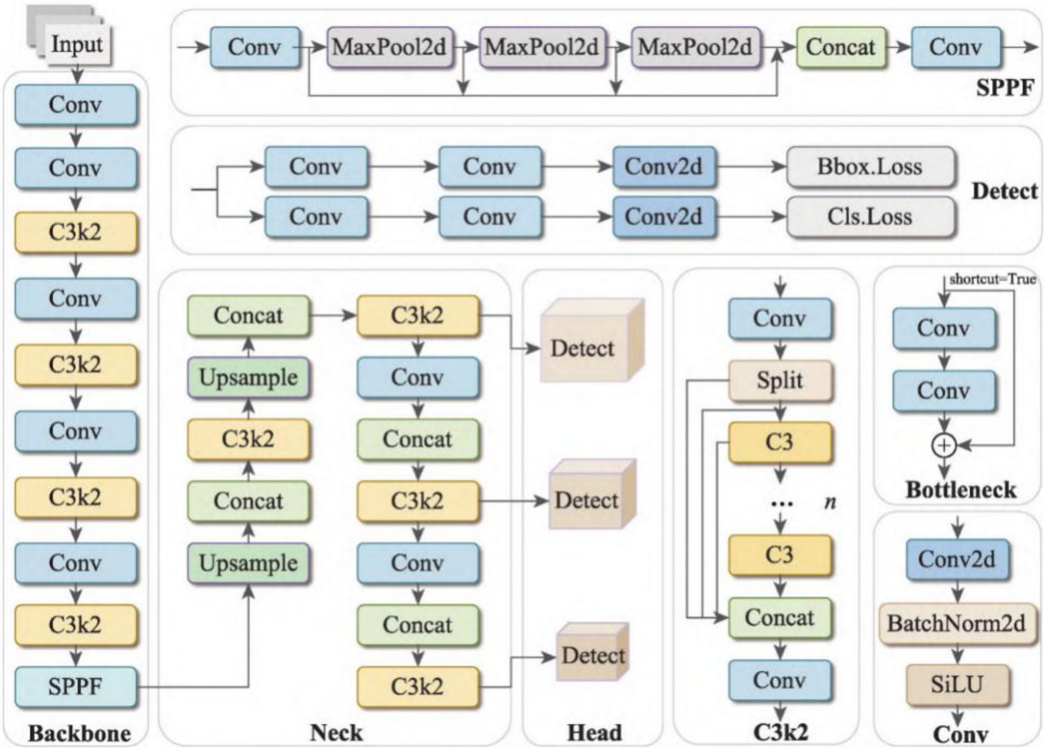



*Figure 4: YOLO v12 model structure*

The neck network fuses the multi-scale features extracted by the backbone network through the Path Aggregation Feature Pyramid Network (PAFPN) structure. FPN fuses different levels of features through top-down and horizontal connections, but its feature fusion mechanism is relatively simple and lacks deep mining of contextual information. PAFPN introduces a bottom-up Path Aggregation Network (PANet) structure based on FPN to significantly enhance its feature aggregation capability. Through bottom-up and top-down path aggregation, PAFPN integrates shallow strong detail information with deep strong semantic information, enhancing multi-scale feature expression capability and achieving efficient feature fusion. Among them, the top-down path concatenates deep and shallow features through upsampling, while the bottom-up path merges shallow and deep features through downsampling. Finally, the three output branches of PAFPN are passed to the head network for further processing.

The head network uses the processed multi-scale feature maps for object detection and classification. It adopts a decoupled head structure to separate the regression branch and the prediction branch, and obtains the category and position information of the target object from the feature maps of different scales to complete the self-labeled classification and localization tasks. In order to further improve efficiency, the network innovatively introduces depthwise separable convolution (DWConv), which significantly reduces the model's parameter count and computational requirements while maintaining high accuracy.

## 4.2 Improvement strategy

### 4.2.1 HGNetV2 backbone network

In the PCB surface defect detection task, the original backbone network of YOLO v12 is difficult to meet the deployment requirements of resource limited scenarios due to its high computational complexity. Therefore, this article introduces the HGNetV2 backbone network based on the RT-DETR model. HGNetV2 is a lightweight design backbone network that uses a hierarchical feature extraction mechanism to learn feature representations of PCB surface defects at different scales. This multi-scale learning ability integrates feature information from different scales, enabling the model to effectively handle detection tasks from microscopic defects to macroscopic defects, thereby enhancing the model's ability to detect targets at different scales and strengthening its robustness to complex backgrounds. For example, in complex industrial environments, defects on PCB surfaces may present multiple sizes and shapes. Multi scale feature fusion can effectively capture these differences and improve the detection accuracy of models for small and large targets. In addition, multi-scale feature fusion can enhance the robustness of the model to complex scenes, especially when facing diverse textures and background noise such as silk screen printing. By fusing features of different scales, the model can better separate targets and backgrounds, reducing false positives and false negatives.

HGNetV2 mainly consists of HGStem preprocessing module, HGBlock data processing module, and depth wise separable convolution (DWConv). (1) HGStem, as the preprocessing module of HGNetV2 network, adopts a combination architecture of multi-level convolution and pooling operations to achieve efficient feature extraction and dimensionality reduction of input data. Before each downsampling, local features of different scales are fused through feature concatenation to complement shallow high-resolution features and deep semantic features. In the process of reducing the resolution of feature maps, injecting low-level features into deep networks through cross layer skip connections significantly enhances the model's ability to respond to small self labeled features. And under strict control of parameter quantity and computational complexity, effective extraction of multi-scale features has been achieved. (2) HGBlock, as the core building block of HGNetV2 network, adopts a parallel hierarchical processing architecture. This module consists of a convolution submodule and a channel compression and decompression submodule connected in parallel, and can capture feature representations at different levels through a hierarchical processing mechanism. Each HGBlock contains multiple levels of feature processing, and each level extracts corresponding scale feature information through a specific range of receptive fields. (3) Depthwise separable convolution. The module integrates multiple sizes of convolutional filters, including lightweight convolution (LightConv) and standard convolution (Conv), to optimize computational efficiency while ensuring feature extraction performance.

Using DWConv instead of regular convolution in HGNetV2 results in lower parameter and computational complexity. For ordinary convolution, it can be expressed as:

$$\begin{cases} P = C_{\text{in}} \times C_{\text{out}} \times K \times K \\ F = C_{\text{in}} \times C_{\text{out}} \times H \times W \times K \times K \end{cases} \tag{4}$$

where, $H$, $W$ and $C_{\text{in}}$ represent the height, width, and number of input channels of the input feature map, $K \times K$ represents the width and height dimensions of the convolution kernel, $C_{\text{out}}$ represents the number of output channels, and $P$ and $F$ represent the parameter and computational complexity of a regular convolution kernel.

For DWConv, the formula is:

$$\begin{cases} P_{DW} = C_{\text{in}} \times K^2 + C_{\text{in}} \times C_{\text{out}} \\ F_{DW} = C_{\text{in}} \times H \times W \times K^2 + C_{\text{in}} \times C_{\text{out}} \times H \times W \end{cases} \tag{5}$$

where, $P_{DW}$ and $F_{DW}$ represent the parameter and computational complexity of DWConv.

From equations (4) and (5), we can obtain:

$$\frac{P_{DW}}{P} = \frac{F_{DW}}{F} = \frac{1}{C_{\text{out}}} + \frac{1}{K^2} \tag{6}$$

According to equation (6), the parameter and computational complexity of DWConv is only $\left(C_{\text{out}} + K^2\right) / C_{\text{out}} K^2$ of ordinary convolution.

As the backbone network of RT-DETR, the original HGNetV2 exhibits excellent detection performance and sufficient flexibility. This article combines the characteristics of YOLO v12 network to optimize HGNetV2 and replace the original YOLO v12 backbone network. Reducing the computational and parameter complexity of the model, thereby achieving lightweighting of the network, while enhancing the robustness of the model.

### 4.2.2 Dynamic convolution improvement HGBlcok

Through the carefully designed HGNetV2 architecture, this article successfully constructed an innovative YOLO V12 backbone network. This network achieves a significant improvement in computational efficiency while significantly reducing the number of model parameters and computational complexity. In order to effectively improve detection accuracy, this article draws on the idea of Dynamicconv and further improves and innovates the HGBlock in the backbone network.

The core idea of Dynamicconv is to introduce more parameters by dynamically combining multiple convolution kernels while maintaining low computational complexity. Meanwhile, as the coefficients of Dynamicconv are dynamically generated based on the input, the network adaptively adjusts the combination of convolution kernels by using dynamic experts to generate convolution weight tensors and dynamic coefficients for different inputs, thereby effectively enhancing the robustness of the model.

Given the input features $\boldsymbol{X} \in \boldsymbol{R}^{C_{\text{in}} \times H \times W}$ and weight tensor $\boldsymbol{W} \in \boldsymbol{R}^{C_{\text{out}} \times C_{\text{in}} \times K \times K}$, traditional convolutional layers can be expressed as follows:

$$\boldsymbol{Y} = \boldsymbol{X} * \boldsymbol{W} \tag{7}$$

where, $\boldsymbol{Y} \in \boldsymbol{R}^{C_{\text{out}} \times H' \times W'}$ is the output of the convolutional layer.

In order to increase the number of parameters in the model, Dynamicconv introduces a parameter enhancement function, which can be expressed as:

$$\boldsymbol{W}' = f(\boldsymbol{W}) \tag{8}$$

where, $\boldsymbol{W}$ is the original weight tensor, $\boldsymbol{W}'$ is the parameter enhanced weight tensor, and *f* is the parameter enhancement function. This function satisfies two basic principles: 1) it does not require excessive computational cost; 2) Can increase model capacity or trainable parameters.

Dynamicconv is implemented through multiple dynamic experts, and a Dynamicconv with *M* dynamic experts can be expressed as:

$$\begin{cases} \boldsymbol{Y} = \boldsymbol{X} * \boldsymbol{W}' \\ \boldsymbol{W}' = \sum_{i=1}^{M} \alpha_i \boldsymbol{W}_i \end{cases} \tag{9}$$

where, $\boldsymbol{W}_i \in \boldsymbol{R}^{C_{\text{out}} \times C_{\text{in}} \times H \times W}$ is the convolutional weight tensor generated by the *i*-th dynamic expert, $\alpha_i$ is the corresponding dynamic coefficient, and $\sum_{i=1}^{M} \alpha_i = 1$ is satisfied.

The coefficient $\alpha_i$ is dynamically generated based on different input samples, and Dynamicconv uses a multi-layer perceptron (MLP) to generate $\alpha_i$ from the input. For the input $\boldsymbol{X}$, global average pooling is applied to fuse the information into a vector, and then the softmax function is used to activate the double-layer MLP module to generate dynamic coefficients. This step can be expressed as follows:

$$\boldsymbol{\alpha} = \text{softmax}(MLP(\text{Pool}(\boldsymbol{X}))) \tag{10}$$

where, $\boldsymbol{\alpha} \in \boldsymbol{R}^{M}$ is a dynamically generated coefficient vector.

For traditional convolutional layers, the parameter and computational complexity are:

$$\begin{cases} \text{Params} = C_{\text{out}} \times C_{\text{in}} \times K \times K \\ FLOPs = W' \times H' \times C_{\text{out}} \times C_{\text{in}} \times K \times K \end{cases} \tag{11}$$

where, Params is the parameter quantity, FLOPs is the computational quantity.

For Dynamicconv, the parameter count and computational complexity are:

$$\begin{cases} \text{Params}' = M \times C_{\text{out}} \times C_{\text{in}} \times K \times K + C_{\text{in}}^2 + M \times C_{\text{in}} \\ FLOPs' = M \times C_{\text{out}} \times C_{\text{in}} \times K \times K + W' \times H' \times C_{\text{out}} \times C_{\text{in}} \times K \times K + C_{\text{in}}^2 + M \times C_{\text{in}} \end{cases} \tag{12}$$

where, Params' is the parameter quantity, FLOPs' is the computational quantity.

Normally, *M* is much smaller than $W' \times H'$, so compared to traditional convolutional layers, Dynamicconv minimizes the increase in FLOPs while introducing as many parameters as possible, while expanding the number of parameters to *M* times, effectively enhancing the model's ability to learn generalized features.

# 5 Experimental analysis

## 5.1 Experimental dataset

With the development of the Internet, online shopping has become the choice of more and more people. More and more people use e-commerce systems to implement online shopping. Its convenience and rapidity have become the first choice for people to shop. According to Alibaba's financial report, the total transaction volume of Alibaba's e-commerce platform exceeded two trillion US dollars in the fiscal year 2024, and the global annual active users reached 960 million. In order to meet the personalized needs of different users on e-commerce platforms, e-commerce platforms will recommend suitable products based on users' interests and hobbies, thus achieving the personalized needs of product sorting for thousands of people. Taobao is a leading enterprise in the e-commerce circle, having created countless miracles, such as the historic breakthrough of 540.3 billion yuan in transaction volume achieved during the "Double Eleven" shopping frenzy in 2024. The Taobao platform is constantly updating and iterating, and its e-commerce platform consumer behavior preference recommendation system provides more personalized services for e-commerce platforms. Therefore, this experiment uses the Taobao public dataset from Alibaba Cloud Tianchi, which includes Taobao rating and review data from November 5, 2024 to December 5, 2024 within one month. The description of the dataset is shown in Table 1. Due to the total number of records exceeding 100 million, which is particularly large, 2 million data points were randomly selected as representative experimental data in the experiment. This part of the data includes the rating and comment records of 761786 users.

*Table 1: Overview of Experimental Dataset*

| Category | Quantity | Attribute Explanation |
|---|---|---|
| Number of users | 47956430 | An integer that represents a user |
| Number of items | 6965624 | An integer that represents a product |
| Number of categories | 765596 | An integer that represents the category which the corresponding item belongs to |
| Number of shops | 4377722 | An integer that represents a shop |
| Number of nodes | 5975349 | An integer that represents a cluster which some items belong to |
| Number of ratings & reviews | 176582732 | An integer that represents ratings & reviews |
| Number of brands | 584181 | An integer that represents a brand |
| Number of interactions | 22516238 | An integer that represents a sample of user-item interaction |
| Data sparsity | 92.75% | A percentage that represents data sparsity |

The fields and their meanings in the experimental dataset are shown in Table 2. The experiment on personalized preference acquisition for e-commerce platforms in this chapter is mainly based on user review text (user_deviewText), product review text (item_deviewText), user rating (user_rating), and product rating (item_rating). The experiment was conducted using a 5-fold cross validation method, with 80% of the data used as the training set and 20% as the testing set.

*Table 2: Meaning of Dataset Fields*

| Field | Field Description | Field | Field Description |
|---|---|---|---|
| user_id | User ID | unixReviewTime | Comment timestamp |
| item_id | Product identification | title | Product Name |
| reviewerName | Username | price | commodity price |
| helpful | Effective evaluation rate | imUrl | Product image link |
| user reviewText | User comment text | related | Related products |
| item reviewText | Product review text | salesRank | Discount information |
| user_rating | User Rating | brand | brand |
| item_rating | product rating | categories | Category |
| summary | comment summary | reviewTime | Comment time |

## 5.2 Result analysis

The main purpose of this chapter's experiment is to verify the performance of the personalized preference acquisition method proposed in this chapter for e-commerce platforms. We calculate the degree of matching between the user preferences of e-commerce platforms and the product lists recommended by the e-commerce platform's consumer behavior pattern preference recommendation system. We compare and analyze the results from two perspectives: different user numbers and the number of different products returned by the recommendation list to the e-commerce platform.

(1) Analysis of experimental results with different numbers of users. When the number of users n takes values of 10, 20, 30, 40, 50, and 60, the accuracy of the algorithm performance is shown in Table 3, the recall rate is shown in Table 4, and the F1 value is shown in Table 5.

*Table 3: Comparison of Accuracy Rates for Different User Numbers*

| Comparison model | Precision@n (n represents the number of users) | | | | | |
|---|---|---|---|---|---|---|
| | n=10 | n=20 | n=30 | n=40 | n=50 | n=60 |
| BPR | 0.0865 | 0.0745 | 0.0634 | 0.0315 | 0.0305 | 0.0305 |
| CF | 0.1143 | 0.1268 | 0.1276 | 0.1270 | 0.1138 | 0.1106 |
| CFN | 0.1652 | 0.1761 | 0.1765 | 0.1765 | 0.1764 | 0.1768 |
| Proposed method | 0.1867 | 0.2387 | 0.2439 | 0.2439 | 0.2429 | 0.2430 |

*Table 4: Comparison of Recall Rates for Different User Numbers*

| Comparison model | Recall @ n (n represents the number of users) | | | | | |
|---|---|---|---|---|---|---|
| | n=10 | n=20 | n=30 | n=40 | n=50 | n=60 |
| BPR | 0.0564 | 0.0764 | 0.0436 | 0.0325 | 0.0314 | 0.0314 |
| CF | 0.0482 | 0.0702 | 0.9913 | 0.9926 | 0.0668 | 0.0536 |
| CFN | 0.0721 | 0.0806 | 0.1021 | 0.1014 | 0.9982 | 0.0834 |
| Proposed method | 0.0996 | 0.1560 | 0.1759 | 0.1538 | 0.1648 | 0.1589 |

*Table 5: Comparison of F1 values for different user numbers*

| Comparison model | F1 measure@n (n represents the number of users) | | | | | |
|---|---|---|---|---|---|---|
| | n=10 | n=20 | n=30 | n=40 | n=50 | n=60 |
| BPR | 0.0682 | 0.0754 | 0.0516 | 0.0312 | 0.0305 | 0.0308 |
| CF | 0.0706 | 0.9915 | 0.1068 | 0.1074 | 0.0842 | 0.0736 |
| CFN | 0.1028 | 0.1128 | 0.1271 | 0.1305 | 0.1274 | 0.1148 |
| Proposed method | 0.1349 | 0.1879 | 0.2031 | 0.1819 | 0.1721 | 0.1854 |

Table 3 shows that as the number of users increases from 10 to 60, the performance of traditional models generally deteriorates: the accuracy of the BPR model drops sharply from 0.0865 to 0.0305, a decrease of 65%; The CF model reached a peak of 0.1276 at n=30 and continued to decline, eventually dropping to 0.1106; Although the CFN model remains relatively stable (0.1761-0.1768), its growth is sluggish. On the other hand, the accuracy of the proposed method exceeded 0.2387 at n=20, an improvement of 35.5% compared to the CFN model, and remained high (0.2429-0.2439) in the subsequent increase in user numbers. This indicates that traditional methods are prone to inaccurate recommendations due to interest conflicts when the user base expands, while the proposed method, through a dynamic preference weight allocation mechanism, can effectively distinguish between users' core needs and edge interests, achieving accurate recommendations.

Table 4 data reveals the differences in recommendation completeness among various models. The recall rate of the BPR model remains below 0.08 and fluctuates sharply with the increase of the number of users; The CF model exhibits an outlier (0.9926) at n=40, which is speculated to be due to data noise or algorithm defects; Although the CFN model reached 0.9982 at n=50, its performance was mediocre in other scenarios (0.0721-0.1021). The proposed method shows a steady growth trend: gradually increasing from 0.0996 for n=10 to 0.1759 for n=30, and maintaining a recall rate of over 15% in subsequent increases in user numbers. This proves that it can more comprehensively explore users' potential interests, especially in multi-user scenarios with stronger interest coverage ability.

The F1 value, as a harmonic average of precision and recall, can more objectively reflect the overall performance of the model. The data in Table 5 shows that the F1 values of BPR and CF models are both below 0.12, and they show a decreasing trend with the increase of user numbers, indicating that they are difficult to balance accurate recommendation and interest coverage. Although the CFN model reaches a peak of 0.1305 at n=40, the overall fluctuation is significant. The proposed method steadily increased from 0.1349 for n=10 to 0.2031 for n=30, and maintained an F1 value of over 17% in subsequent increases in user numbers. For example, when n=60, its F1 value (0.1854) increased by 61.5% compared to the CFN model (0.1148), proving that the proposed method can achieve better precision coverage balance in complex user scenarios.

When the personalized recommendation list of e-commerce platforms returns different numbers of products with K values of 5, 10, 15, 20, 25, and 30, the accuracy of the algorithm performance is shown in Figure 5, the recall rate is shown in Figure 6, and the F1 value is shown in Figure 7.

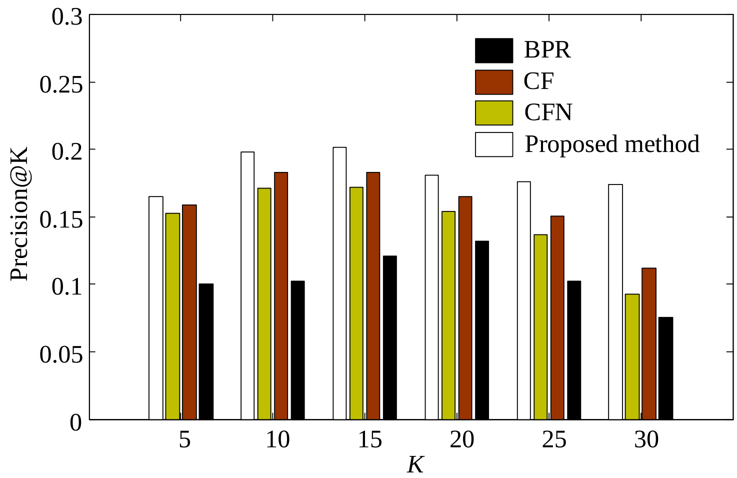



*Figure 5: Comparison of Accuracy of Different Product Numbers in the Recommended List*

At the level of accuracy, given the numerical values of products returned from different recommendation lists, it can be seen that the algorithm proposed in this paper has significant advantages over the benchmark model at each node. The algorithm proposed in this article has improved by 52.9% compared to BPR, 7.95% compared to CF, and 14.98% compared to CFN. From Figure 5, it can be seen that the accuracy of CF exceeds that of BPR and CFN. This is because in the case of sparse data, user ratings can reflect better user preferences, which is consistent with previous research.

At the recall level, given the numerical values of products returned from different recommendation lists, it can be seen that the algorithm proposed in this paper has a significant advantage over the benchmark model as a whole. However, there is also a phenomenon where when K is assigned a value of 25, it is exceeded by CF. This is because as the number of neighbors of rating users increases, the collaborative filtering algorithm will experience an increase in recall rate, but it will quickly decrease after data sparsity. We compared and analyzed with the best results, and found that the recall rate of the algorithm proposed in this article improved by 52.68% compared to BPR, 17.53% compared to CF, and 34.68% compared to CFN.

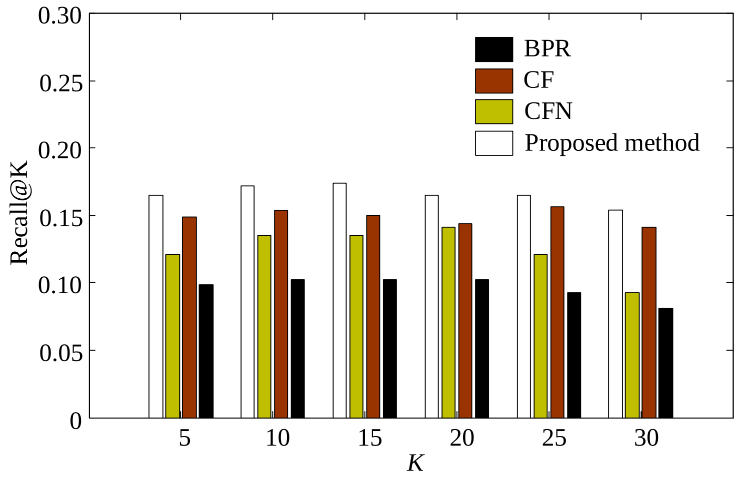



*Figure 6: Comparison of recall rates for different product numbers in the recommended list*

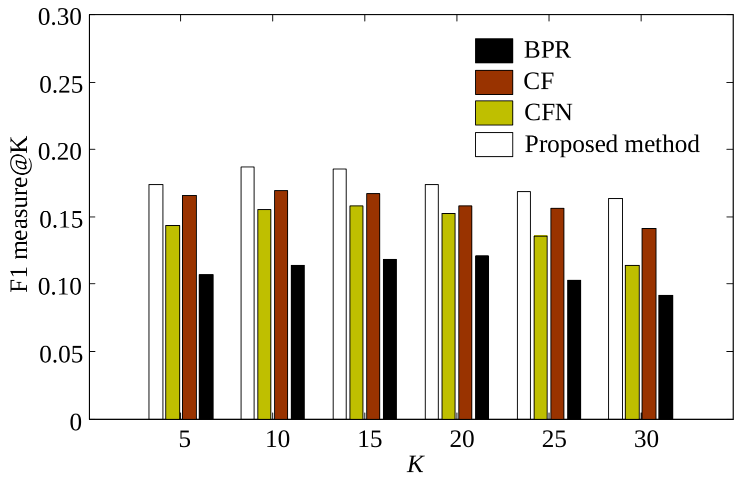



*Figure 7: Comparison of recall rates for different product numbers in the recommended list*

At the F1 value level, given the numerical values of products returned by different recommendation lists, the algorithm proposed in this paper has significant advantages compared to benchmark models. We have compared and analyzed the best results, and found that the F1 value of the algorithm proposed in this article has increased by 51.87% compared to BPR, 9.64% compared to CF, and 17.58% compared to CFN.

Overall, from Figures 5, 6, and 7, it can be seen that as the recommended list returns different values for the number of products, the accuracy, recall, and F1 value of the algorithm proposed in this paper are all due to the comparison of the three benchmark models, indicating that the preference acquisition and personalized recommendation performance of the model in this chapter are good. Meanwhile, compared to the benchmark model, the accuracy, recall, and F1 value curves of the algorithm proposed in this paper are relatively smooth, indicating that the stability of the algorithm proposed in this paper is good. In addition, when the recommended list returns a value of 10 for the number of products K, the accuracy, recall, and F1 value of the algorithm proposed in this paper all reach their peak, indicating that the model convergence efficiency of this algorithm is high and meets the requirements of general e-commerce platform consumer behavior pattern preference recommendation systems.

# 6 Conclusion

Against the backdrop of rapid development of the digital economy, cross-border e-commerce platforms have become an important channel for global consumers to shop. However, with the surge in user numbers and the increasing variety of products, the problem of information overload has become more severe. Accurately capturing changes in user behavior patterns and recommending products that match their preferences has become the key to improving user experience and platform competitiveness. This article proposes a personalized recommendation method based on the Deep Incremental Recommendation (DIR) model to address this issue, aiming to achieve an effective balance between accurate recommendation and interest coverage through dynamic weight allocation and multi-scale feature fusion. Firstly, in response to the characteristics of changes in user behavior patterns on cross-border e-commerce platforms, a deep incremental recommendation model was constructed. Through collaborative training of the basic model and incremental model, the model effectively utilized historical data prediction errors and incremental data sorting errors to optimize parameters, improving its adaptability and generalization ability. Secondly, combining the idea of dynamic convolution, the HGNetV2 backbone network was improved by dynamically combining multiple convolution kernels, enhancing the model's ability to learn generalized features while reducing computational complexity. In addition, this article also introduces the Path Aggregation Feature Pyramid Network (PAFPN) structure, which improves the feature fusion ability and further enhances the detection performance of the model through bottom-up and top-down path aggregation.

Although this article has achieved certain results in personalized recommendations for cross-border e-commerce platforms, there are still some issues worth further research. Future work will revolve around the following aspects: firstly, exploring more types of user behavior data, such as browsing history, click behavior, etc., to more comprehensively capture user preferences; The second is to study how to integrate contextual information (such as time, location, social relationships, etc.) into recommendation models to improve the timeliness and personalization of recommendations; The third is to consider how to apply the model proposed in this article to other types of e-commerce platforms or recommendation scenarios to verify its universality and scalability. Through continuous in-depth research and practical application, we are expected to provide users with more accurate and personalized recommendation services, promoting the sustainable development of cross-border e-commerce platforms.

# Author's Profile

LiYe was born in Jiangxi, Pingxiang. China, in 1992. She graduated with a master's degree from Jiangxi University of Finance and Economics, and is currently at Guangzhou College of Commerce. She main research direction is cross-border e-commerce and consumer behavior.

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