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Retraction

Retracted: Personalized Recommendation of Online Shopping Products Based on Online Fast Learning through Latent Factor Model

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Shi, "Personalized Recommendation of Online Shopping Products Based on Online Fast Learning through Latent Factor Model," *Advances in Multimedia*, vol. 2022, Article ID 9292874, 11 pages, 2022.

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Research Article

Personalized Recommendation of Online Shopping Products Based on Online Fast Learning through Latent Factor Model

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In order to improve the personalized recommendation effect of online shopping products, this article combines online fast learning through latent factor model to construct a personalized virtual planning recommendation system for online shopping products. Moreover, this article improves on the ONMTF model. In the problem of cross-domain recommendation, this article clusters users and items in each data domain with hidden scoring patterns and learns common scoring patterns that can be shared between different data domains to deal with the data sparse problem that often occurs in recommender systems. The experimental research results show that cross-domain recommendation can indeed use the implicit semantics or topics between domains to share information and knowledge, thereby improving the accuracy of recommendation.

1. Introduction

Online shopping websites provide consumers with a virtual shopping space with free choice, low price, and no time and space constraints. However, while online shopping brings convenience and benefits to consumers, due to the virtual nature of the online shopping environment, the inaccessibility of products, the fact that the transaction process is not face-to-face, and the uncertainty of online shopping, online shopping consumers are prone to regret. The powerful search engine has led to the rapid searchability of product information, and it is also aggravating the generation of consumer regret. Compared with traditional shopping methods, regret is not only related to the products or services consumers choose but also to the environment and methods of online shopping.

Online shopping, as the name implies, is the selection and purchase of products or services through the Internet. It is mainly to search for product information through a search engine on the Internet and to issue shopping needs through online ordering and online banking or cash on delivery. Then the manufacturer or online retailer will deliver the goods by mail order or by courier company. Online shopping is an e-commerce activity aimed at consumer customers rather than productive customers, so it belongs to the category of B2C e-commerce. Due to the special shopping environment, online shopping has certain process differences from traditional shopping methods. For example, consumers cannot receive the products immediately, so they cannot immediately experience the fun of shopping, and there is also the process of online product selection. There is more information available about the product than ever before, so it is not just necessary to consider the factors of the product.

Some user reviews can be manipulated by sellers, resulting in distorted information. At the same time, a large number of counterfeit goods affect the normal sales of genuine brands. In the process of online payment, personal information security issues, bank account passwords, and fund security in the transfer process are also factors that hinder the development of online shopping. In addition, there are also logistics and distribution problems in online shopping, that is, some logistics companies deliver faster, while others are slower. The speed of logistics and delivery directly affects the purchasing experience of online buyers. At this time, shopping satisfaction cannot be directly experienced, and it is often delayed for 2 to 3 days to experience the joy of shopping.

In order to improve the personalized recommendation consumption experience of online shopping products, this article combines online fast learning through latent factor model to construct a virtual planning recommendation system for online shopping products and promotes the recommendation effect of subsequent online shopping products.

2. Related Works

This article focuses on the influence of the level of expectations that consumers have on the changes in consumers' dynamic choices [1]. For those consumers whose expected performance level is uncertain, when the performance of the product experienced or observed by the consumer is consistent with the original expectation, and for those risk-averse consumers who are uncertain about the initial expected performance, the willingness to buy a higher commodity will be greatly enhanced, and for those consumers who are risk-averse, the willingness to buy the product will be reduced [2]. The increase in consumers' purchasing experience will reduce the uncertainty of consumers' expected performance level of purchasing products. Through experimental research, it is confirmed that consumers will experience satisfaction and regret at the same time. On this basis, it is further confirmed that consumers' regret influences the negative word of the purchased brand and the positive word of the brand they gave up. In other words, consumer regret will increase the spread of both [3]. Studies have shown that the quality of the relationship between consumers and their chosen brands (including satisfaction, trust, and commitment) significantly moderates the intensity of regret [4]. The effect of order effect on consumer regret has been studied. For example, after adjusting the order of comparison, consumers have different degrees of regret [5]. We explore the loss of perceived value due to price changes, which leads to an increase in the intensity of consumer regret, and examine the effect of regret on consumer complaints. Studies have shown that the larger and faster the price cut is, the more the consumer will regret it [6]. Regret will produce consumers' private complaints, complaints to manufacturers, and a series of boycott behaviors. Statistical analysis is carried out on consumers' regret after purchasing products through empirical methods, and its influencing factors are studied [7]. Research shows that consumer regret has a significant positive impact on both complaints and switching behaviors; trust and commitment have a significant buffering effect on regretful switching behaviors [8]. Based on the diminishing sensitivity theory of prospect and the theory of two information processing modes, the relationship strength between consumers' regret intensity and changes in post-purchase comparison results was confirmed through scenario simulation experiments [9]. Experiments show that post-purchase outcome comparisons that vary within a certain range do not lead to significant changes in consumer regret [10]. This article explores the source and explanation of sunk costs and argues that individual regret avoidance is the cause of sunk costs, which can be explained by the consistency model of regret. The cost that an individual has already paid for a certain commodity or service is known as a sunk cost, and it has the effect of increasing how frequently individuals utilize the commodity or service [11]. The method of factor analysis was used to explore six main influencing factors of tourists' regret: family and friends, tourism commodity performance, marketing, surrounding tourists, impulse purchase, and resource constraints [12].

Literature [13] believes that consumers' shopping decisions mainly have four stages: the first stage is the formation of consumer attitudes according to the product information provided by the manufacturer; the second stage is the consumer's information collection and product evaluation stage; The third stage is when consumers put their purchasing motives into action; the fourth stage is the consumer's information feedback stage. At this stage, the manufacturer can adjust the product through the consumer's feedback information. The Howard-Sheth model defines customer satisfaction as a kind of cognition of consumers and cognition of whether their pay and return are appropriate, if appropriate, the degree of satisfaction will be higher [14]. The shopping decision-making process of consumers is the process of consumers' cognition of the purchased products. Literature [15] proposed a simulation model is an explanatory model, which believes that there are five main processes in the shopping process of consumers: the first process is demand recognition, the second process is information search, the third process is selective evaluation, the fourth process is the purchase, and the fifth process is the post-purchase evaluation. The model still assumes that consumers are rational and fully considers the consistency between consumers' purchase expectations and purchase effects, which has a certain guiding significance for the prediction of consumers' decision-making behavior [15]. Considering the influence of virtual interaction characteristics of the online shopping environment on consumers—it is difficult for consumers to make in-depth evaluation and selection of all available products—a two-stage theory is proposed. This theory believes that the shopping decision-making process of online shopping consumers mainly has two stages. The first stage is the information browsing stage. In this stage, consumers will browse product information and choose some products from a large number of products that can be further compared. The second stage is the purchase decision stage. In this stage, consumers mainly make further choices from the products that have been selected in the first stage, and the selection is based on the aspects that consumers pay more attention to [16]. Based on the theory of rational behavior of consumers, this article proposes the technology acceptance model (TAM), which mainly studies the main influencing factors of individuals accepting or rejecting information systems and explains the relationship between users' beliefs, attitudes, intentions, and actual behaviors. Consumers' behavioral intentions are affected by attitudes and perceived usefulness, attitudes are affected by perceived usefulness and perceived ease of use, and perceived usefulness is affected by perceived ease of use [17].

3. Online Fast Learning through Latent Factor Model

We assume that there is a rating matrix X∈R$^{M\times N}$, where M and N represent the number of users and items, respectively. For the ONMTF model, its role is to decompose the matrix X into three nonnegative matrices (also called factors): U∈RM × K, $\sum \in R^{K\times L}$, and $V \in R^{N\times L}$, so that $X \approx$ USV^T. This approximation can be solved by the following optimization problem:

$$\min_{U,\Sigma,V\geq 0}\left\| X - U\Sigma V^T \right\|, \tag{1}$$

where $\|\cdot\|$ refers to the Frobenius norm of the matrix. We assume that there is a matrix A, and the element is $a_{ij}, i \in [1, m], j \in [1, n]$, then the F norm of the matrix is defined as shown in the following formula:

$$\|A\|_F = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|a_{ij}\right|^2}. \tag{2}$$

The three matrices of the objective function of the ONMTF model can be updated iteratively with the following formulas:

The update U is: the model fixes V and $\sum$ and then updates U according to the following formula:

$$U_{ik} \leftarrow U_{ik}\sqrt{\frac{\left(XV\Sigma^T\right)_{ik}}{\left(UU^T XV\Sigma^T\right)_{ik}}}. \tag{3}$$

The update V is: The model fixes U and $\sum$ and then updates V according to the following formula:

$$V_{ik} \leftarrow V_{ik}\sqrt{\frac{\left(X^T U\Sigma\right)_{jk}}{\left(VV^T X^T U\Sigma\right)_{jk}}}. \tag{4}$$

The update $\sum$ is: The model fixes U and V and then updates $\sum$ according to the following formula:

$$\Sigma_{ik} \leftarrow \Sigma_{ik}\sqrt{\frac{\left(U^T XV\right)_{ik}}{\left(U^T U\Sigma V^T V\right)_{ik}}}. \tag{5}$$

The matrix decomposed by ONMTF is explained below from the perspective of clustering:

$U = [u_1, \ldots, u_k]$ represents the hidden user factor, in which each u is an M-dimensional vector, which represents the product preference distribution of M users.

$\sum = [\sigma_1, \ldots, \sigma_L]$ is a $K \times L$-dimensional matrix, which represents the scoring characteristics of K-type users for work-type items. oy can represent the preference of the main category of users to the jth category of items.

$V = [v_1, \ldots, v_L]$ represents the hidden item factor, in which each u is an IV-dimensional vector, which represents the distribution of the first category in the L category that N users gather for IV items.

The ONMTF model can cluster items and users at the same time and can mine the relationship between items and users in units of classes, eliminating the influence of some abnormal individuals, so the effect is better than some other latent factor models. The algorithm used by the OVCLDA model we propose in section 3 is also a topic that simultaneously learns multiple discrete datasets and can relate the various domains. The multinomial distribution w learned from OVCLDA can represent the distribution of a word or document over different datasets. Some of these distributions are relatively uniform, and some have a probability close to 1 on a dataset. Uniform distribution means that the information of the topics reflected by the corresponding words can be shared in different datasets, while nonuniform distribution can be regarded as preserving the unique topic distribution on some datasets. Similarly, in cross-domain recommendation problems, mutually related datasets can share common latent topics, but the unique features in each domain should also be properly preserved. Such peculiar features can refer to user categories whose interests are different from those of users in other data domains, or that item categories have a low correlation with items in other domains.

We assume that there are multiple user rating matrices, and the user and item information between these matrices is related at the class level. r is the index of the domain, and $\tau \in [1, t]$. There is a rating matrix D in the ┌th domain, where the set of users is $X_\tau = \left\{x_1^\tau, \ldots, x_{M_\tau}^\tau\right\}$, and the set of items is $Y_\tau = \left\{y_1^\tau, \ldots, y_{N_\tau}^\tau\right\}$, where M and N represent the number of rows (users) and columns (items) of the matrix, respectively. Some of the user items in some datasets here may overlap with others or they may be completely unrelated. However, in the absence of a clear correspondence between user IDs and item IDs, we can only assume that all user items do not overlap, and the overlap here only refers to the case of the same ID.

Each scoring matrix has some scoring data and missing data. Therefore, we need a binomial weight matrix W, whose number of rows and columns is exactly the same as that of matrix D. However, if $[D]y$ has observations, then $[W.]y = 1$; if there are no observations, then $[W.]yf = 0$. We refer to the matrix that needs to predict the score as the target matrix, and the other matrices as auxiliary matrices. Therefore, the problem of this chapter is how to learn effective information and knowledge from the associated auxiliary matrix to predict the missing values in the target matrix.

Existing cross-domain recommendation models generally believe that cross-domain hidden cluster-level structures can be extracted from the rating matrix of user groups for item categories, and this can cluster items and users together and get the connections between them. We can also admit that knowledge can be shared between domains to collectively cluster items and users. Therefore, if you want to get the score matrix clustering in the ┌th domain, you can use the ONMTF model to get the following objective function:

$$\min_{U_\tau,\Sigma_\tau,V_\tau\geq 0}\left\|\left[D_\tau - U_\tau^*\Sigma V_\tau^T\right]\circ W_\tau\right\|^2, \tag{6}$$

where $V_\tau \in R^{N_\tau \times L_\tau}$ represents the Q item classes in the Tth domain. $\sum_\tau^* \in R^{M_\tau \times L_\tau}$ represents the rating pattern of the kth user category to the lth item category in the rth domain, each element [>]ua in this matrix is the average of the scores between the corresponding user item categories. W is a binomial weight matrix, and the symbol o represents the entry-wise product of the corresponding elements of the matrix. When involving multiple related data domains containing different sets of users or items, it can be assumed that different domains have similar scoring patterns or that similar topics can be shared across domains.

In general, it is difficult to obtain clear associations between users in different data domains. For example, on movie rating and book rating sites, movies and books can be considered to have similar categories or themes, because the two items have similar attribute information (such as tragedy or comedy, etc.). However, on various other websites, the user groups may retain the unique interest characteristics in their respective domains, showing different scoring modes. For example, rating information for Oscar-winning movies does not necessarily help cluster books on the subject of Oscar history. For this reason, we relax the assumptions in the article, arguing that users in different domains can have similar clusters but items in each domain can retain their domain-specific clustering patterns.

We need to improve on the original ONMTF model so we divide the cross-domain implicit rating pattern into two parts: commonality and feature, that is, $\sum_\tau^* = [\sum_0, \sum_\tau]$. Among them, $\sum_0 \in R^{K_\tau \times T}$, $\sum_\tau \in R^{K_\tau \times (L_\tau - T)}$, T represent the dimension of the shared common scoring pattern, and $(L_\tau - T)$ represents the dimension of the unique scoring pattern in the domain. To facilitate the following discussion, we name the improved method DSSCM (domain similar and specific clustering model). Figure 1 is the same graphical style of domain similar and specific clustering model. From the figure, we can be seen the operation process of this model. The parameters in the figure will also be explained later.

The common part $\sum_0$ of the scoring mode of the model can obtain similar behaviors of the user group when facing T categories of related commodities from different fields. This can help solve the data sparsity problem that often occurs in traditional recommendation situations. The characteristic part $\sum_r$ of the model scoring mode can distinguish the different scores of the $(L_\tau - T)$ category items by the user group, which can also reveal the connection between multiple domains and improve the accuracy of the recommendation.

Therefore, in each domain, the DSSCM model can learn the latent factor $U_\tau \in R^{K_\tau \times M_\tau}$ of the user group, where $K_\tau = K$. The latent factor of the item group is $V_\tau = [V_{\tau 0}^T, V_{\tau 1}^T] \in R^{T \times N_\tau}$, where $V_{\tau 0} \in R^{T \times N_\tau}$ corresponds to the topic shared in the item group, and $V_{\tau 1} \in R^{(L_\tau - T) \times N_\tau}$ corresponds to the specific topic of the item group in the τth domain. The objective function of the DSSCM model is expressed as shown in the following formula:

$$\min_{U_\tau, \Sigma_0, \Sigma_\tau, V_\tau \geq 0} \left\| \left[D_\tau - U_\tau [\Sigma_0, \Sigma_\tau] V_\tau^T \right] \circ W_\tau \right\|^2. \tag{7}$$

In addition, in order to make the latent factor more accurate, we need to add some prior knowledge in the training process of the model. For example, we add & normalization restrictions to each row in U_τ and V_τ, that is, $U_\tau 1 = 1$, $V_\tau 1 = 1$.

It is worth noting that Figure 1 is a special case of the DSSCM model. In fact, the CBT model does not consider the unique scoring mode in each domain but only considers the shared scoring mode across domains.

We use an alternating minimization algorithm to optimize the objective function 7 of the model until convergence. Simple without loss of generality, $\tau = 2$ is set. Therefore, the general formula (7) can be rewritten as:

$$\begin{aligned} \min_{U_\tau, \Sigma_0, \Sigma_1, \Sigma_2, V} & f \left\| \left[D_1 - U_1 [\Sigma_0, \Sigma_1] V_1^T \right] \circ W_1 \right\|^2 \\ & + \left\| \left[D_2 - U_2 [\Sigma_0, \Sigma_2] V_2^T \right] \circ W_2 \right\|^2. \end{aligned} \tag{8}$$

Then, the following formula is established:

$$\begin{aligned} U_1 1 &= 1, \\ U_2 1 &= 1, \\ V_1 1 &= 1, \\ V_2 1 &= 1, \end{aligned} \tag{9}$$

where

$$\begin{aligned} U_1 &\in R^{M_1 \times K}, \\ U_2 &\in R^{M_2 \times K}, \\ V_1 = \left[V_{10}^T, V_{11}^T \right] &\in R^{N_1 \times L_1}, \\ V_2 = \left[V_{20}^T, V_{21}^T \right] &\in R^{N_2 \times L_2}, \\ \Sigma_0 &\in R^{K \times T}, \\ \Sigma_1 &\in R^{K \times (L_1 - T)}, \\ \Sigma_2 &\in R^{K \times (L_2 - T)}. \end{aligned} \tag{10}$$

The objective function is optimized using the alternate multiplicative updating algorithm, which is used in nonnegative matrix factorization to ensure the nonnegativity of the latent factors. The objective function is non-convex for the variables $U, \sum_0, \sum_1, \sum_2$ and V. Therefore, in the process of optimizing the objective function, the alternate update algorithm updates the parameters of a certain set when other parameter variables remain unchanged, and so on to the variables of other sets. Repeating this process multiple times can make the algorithm converge. The following is the formula for each variable to update iteratively in turn:

(1) The algorithm learns $\sum_1$. Taking learning $\sum_1$ as an example, the following will give how to optimize the target parameter when other parameter factors are fixed. First, we rewrite formula (8) into the following form:

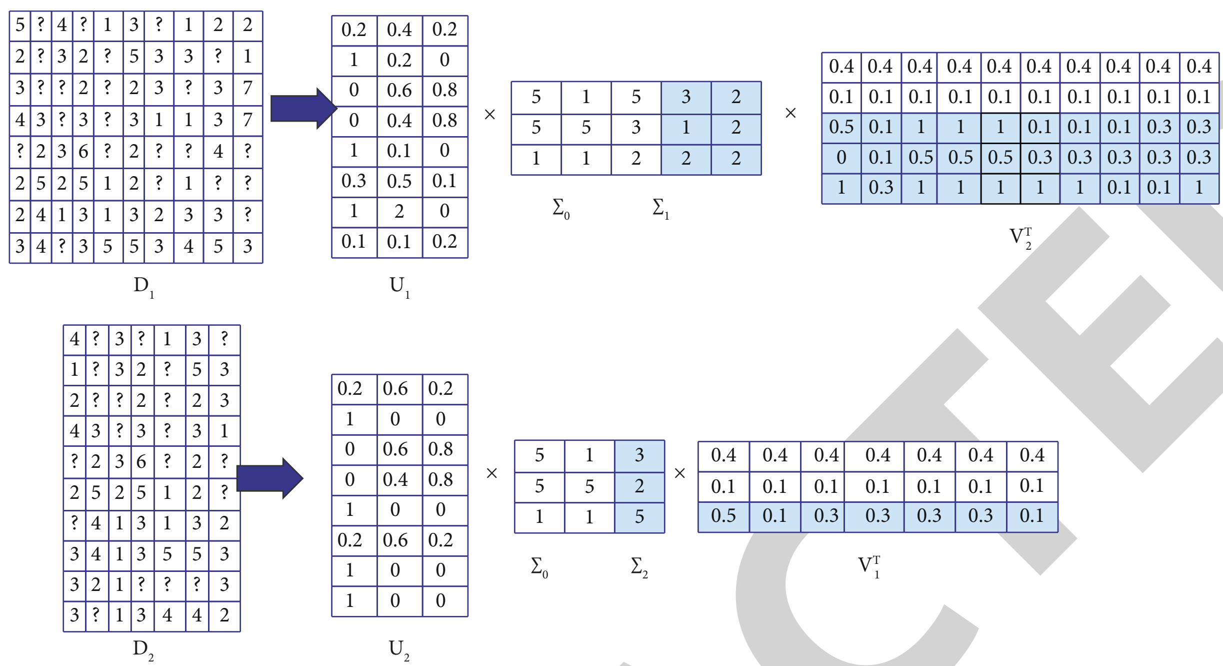

Figure 1: Illustration of the DSSCM model.

$$\min_{\Sigma_1} f(\Sigma_1)\left\| [D_1 - U_1\Sigma_0 V_{10} - U_1\Sigma_1 V_{11}] \circ W_1 \right\|^2 + \left\| [D_2 - U_2\Sigma_0 V_{20} - U_2\Sigma_2 V_{21}] \circ W_2 \right\|^2. \tag{11}$$

Then, we take the partial derivative with respect to $f(\sum_1)$:

$$\frac{\partial f(\Sigma_1)}{\partial \Sigma_1} = 2\Big(U_1^T\big(|U_1\Sigma_0 V_{10}| \circ W_1\big)V_{11}^T - U_1^T(D_1 \circ W_1)V_{11}^T\Big) + 2U_1^T\big(|U_1\Sigma_1 V_{11}| \circ W_1\big)V_{11}^T. \tag{12}$$

Then, using the KKT (Karush–Kuhn–Tucker) condition for nonnegative $\sum_1$, and $(\partial f(\sum_1)/\partial \sum_1) = 0$, we can obtain the following update rule for $\sum_1$:

$$\Sigma_1 \leftarrow \Sigma_1 \sqrt{\frac{U_1^T(D_1 \circ W_1)V_{11}^T}{U_1^T\big(|U_1\Sigma_0 V_{10}| \circ W_1\big)V_{11}^T + U_1^T(D_1 \circ W_1)V_{11}^T}}. \tag{13}$$

(2) The algorithm learns $\sum_2$. Similarly, the latent factor $\sum_2$ can be learned. The following are the rules for updating $\sum_2$:

$$\Sigma_2 \leftarrow \Sigma_2 \sqrt{\frac{U_2^T(D_2 \circ W_2)V_{21}^T}{U_2^T\big(|U_2\Sigma_0 V_{20}| \circ W_2\big)V_{21}^T + U_2^T(D_2 \circ W_2)V_{21}^T}}. \tag{14}$$

(3) The algorithm learns $\sum_0$. The following formula gives the rules for learning the latent factor $\sum_0$:

$$\Sigma_0 \leftarrow \Sigma_0 \sqrt{\frac{U_1^T(D_1 \circ W_1)V_{10}^T + U_2^T(D_2 \circ W_2)V_{20}^T}{A + B}},$$
$$A = U_1^T\big(|U_1\Sigma_0 V_{10}| \circ W_1\big)V_{10}^T + U_1^T\big(|U_1\Sigma_1 V_{11}| \circ W_1\big)V_{10}^T,$$
$$B = U_2^T\big(|U_2\Sigma_0 V_{20}| \circ W_2\big)V_{20}^T + U_2^T\big(|U_2\Sigma_2 V_{20}| \circ W_2\big)V_{20}^T. \tag{15}$$

(4) The algorithm learns U_1. The following formula gives the rules for learning the latent factor U_1:

$$U_1 \leftarrow U_1 \sqrt{\frac{(D_1 \circ W_1)V_1[\Sigma_0, \Sigma_1]^T}{\big([U_1[\Sigma_0, \Sigma_1]V_1^T] \circ W_1\big)V_1[\Sigma_0, \Sigma_1]^T}}. \tag{16}$$

(5) The algorithm learns U_2. The following formula gives the rules for learning the latent factor U_2:

$$U_2 \leftarrow U_2 \sqrt{\frac{(D_2 \circ W_2)V_2[\Sigma_0, \Sigma_2]^T}{\big([U_2[\Sigma_0, \Sigma_2]V_2^T] \circ W_2\big)V_2[\Sigma_0, \Sigma_2]^T}}. \tag{17}$$

(6) The algorithm learns V_1. The following formula gives the rules for learning the latent factor V_1:

$$V_1 \leftarrow V_1 \sqrt{\frac{[\Sigma_0, \Sigma_1]^T U_1^T(D_1 \circ W_1)}{[\Sigma_0, \Sigma_1]^T U_1^T\big([U_1[\Sigma_0, \Sigma_1]V_1^T] \circ W_1\big)}}. \tag{18}$$

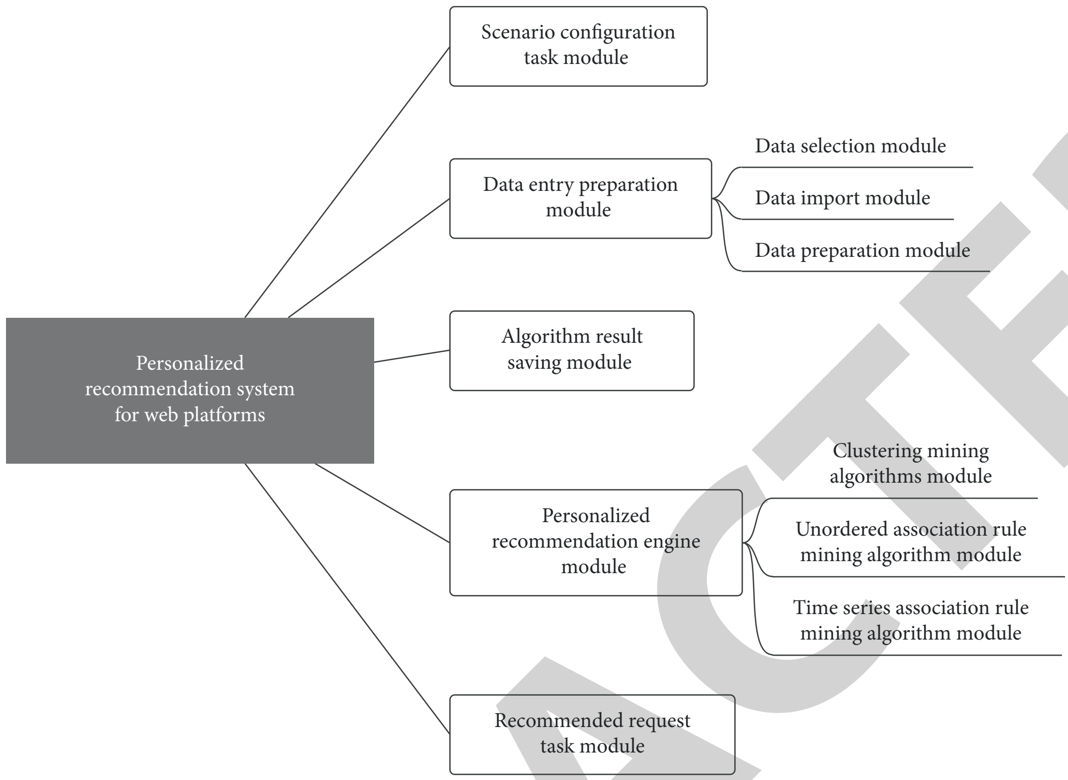

Figure 2: The overall function block diagram of the system.

It is worth noting that $V_{10}^T = V_1(:, 1: T)$, $V_{11}^T = V_1(:, (T+1): L_1)$.

(7) The algorithm learns V_2. The following formula gives the rules for learning the latent factor V_2:

$$V_2 \leftarrow V_2 \sqrt{\frac{[\Sigma_0, \Sigma_2]^T U_2^T (D_2 \circ W_2)}{[\Sigma_0, \Sigma_2]^T U_2^T \left(\left[U_2 [\Sigma_0, \Sigma_2] V_2^T\right] \circ W_2\right)}}. \tag{19}$$

It is worth noting that $V_{20}^T = V_2(:, 1: T), V_{21}^T = V_1(:, (T+1): L_2)$.

Using the above update rules, $\sum_0$ in formula (13), $\sum_1$ in formula (11), $\sum_2$ in formula (12), U_1 in formula (14), U_2 in formula (15), V_1 in formula (16), and V_2 in formula (17) are updated, respectively. The value of the objective function will decrease monotonically and finally reach convergence. The proof of the convergence of the above iteration rule can be referred to.

4. Personalized Recommendation of Online Shopping Products Based on Online Fast Learning through Latent Factor Model

The system is divided into data input preparation module, personalized recommendation algorithm module, algorithm result storage module, scene configuration function module, and recommended task module according to business requirements and functional requirements (Figure 2). According to the needs of the entire personalized recommendation system for online shopping platforms, this article develops the main process of the personalized recommendation system, including: data preprocessing, personalized algorithm recommendation algorithm module, data export, algorithm configuration, and recommendation request. The personalized recommendation algorithm module is mainly for the research and development of algorithms, mainly including association rules and the realization of massive data processing of cluster mining-related algorithms.

This system has no user interface, and it is not that the users of the online shopping platform directly interact with the system but the users interact with the system through other systems. There are two main ways that the external system interacts with this personalized recommendation system. One is to interact with the GP database and use the algorithm operation results of the personalized recommendation system by taking the data output by the algorithm operation. The other is to interact by calling the method in the recommendation request task module. The function of the recommendation request task module is to implement the recommendation combination logic of a series of scenarios. The architecture of the system is shown in Figure 3.

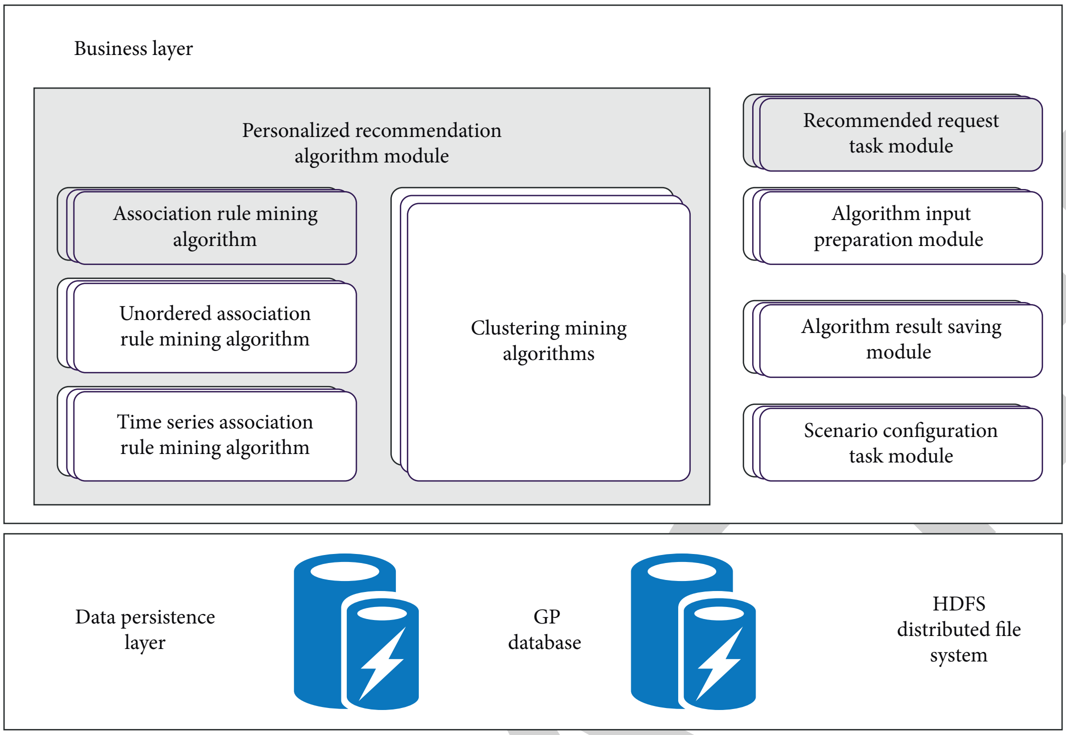

FIGURE 3: Structure diagram of the system architecture.

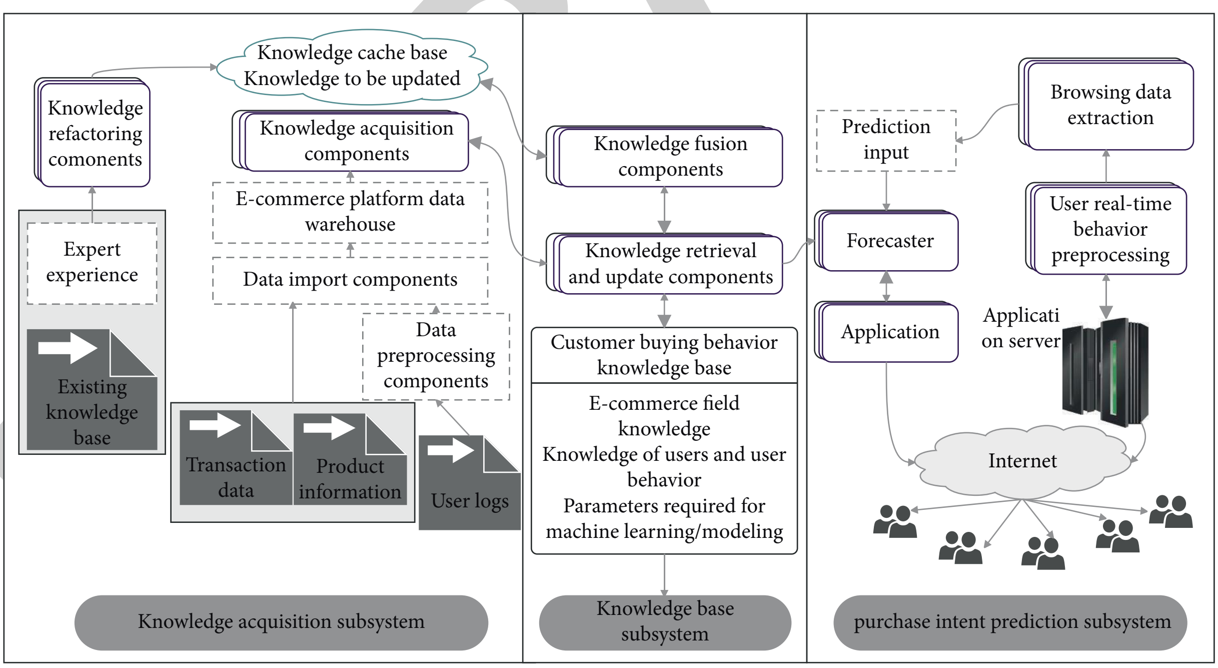

FIGURE 4: Architecture diagram of e-commerce customer purchase intention prediction system.

The architecture of the e-commerce customer purchase intention prediction system is shown in Figure 4. The main function of the knowledge acquisition subsystem in the figure is to acquire knowledge for customer intention prediction from customer transaction data and transmit the acquired knowledge to the knowledge base subsystem. The main function of the knowledge base subsystem is to organize and manage the knowledge acquired by the knowledge acquisition subsystem and to provide the knowledge support required for the prediction for the customer

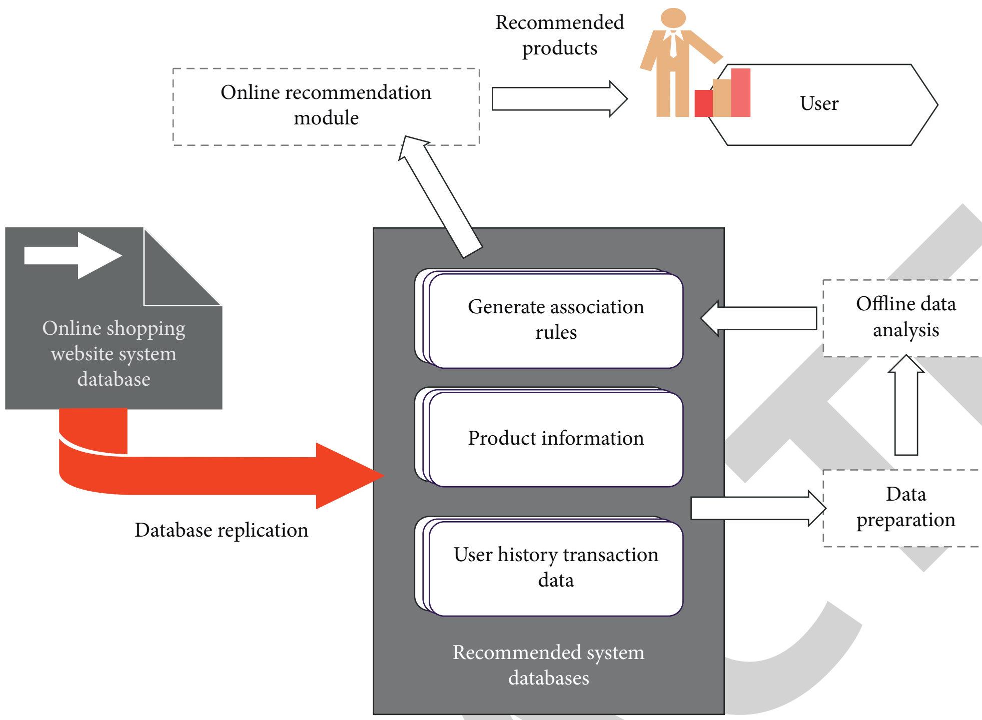

Figure 5: Architecture diagram of online shopping recommendation system.

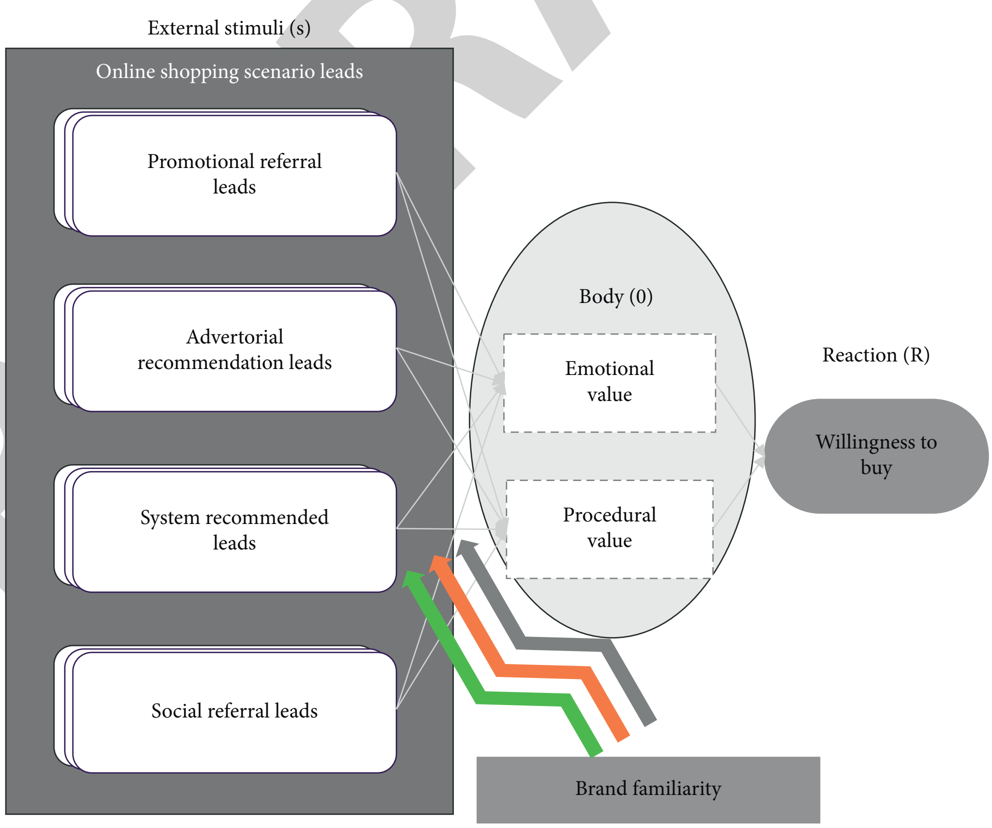

Figure 6: Research model on the influence of online shopping situational cues on consumers' purchase intention.

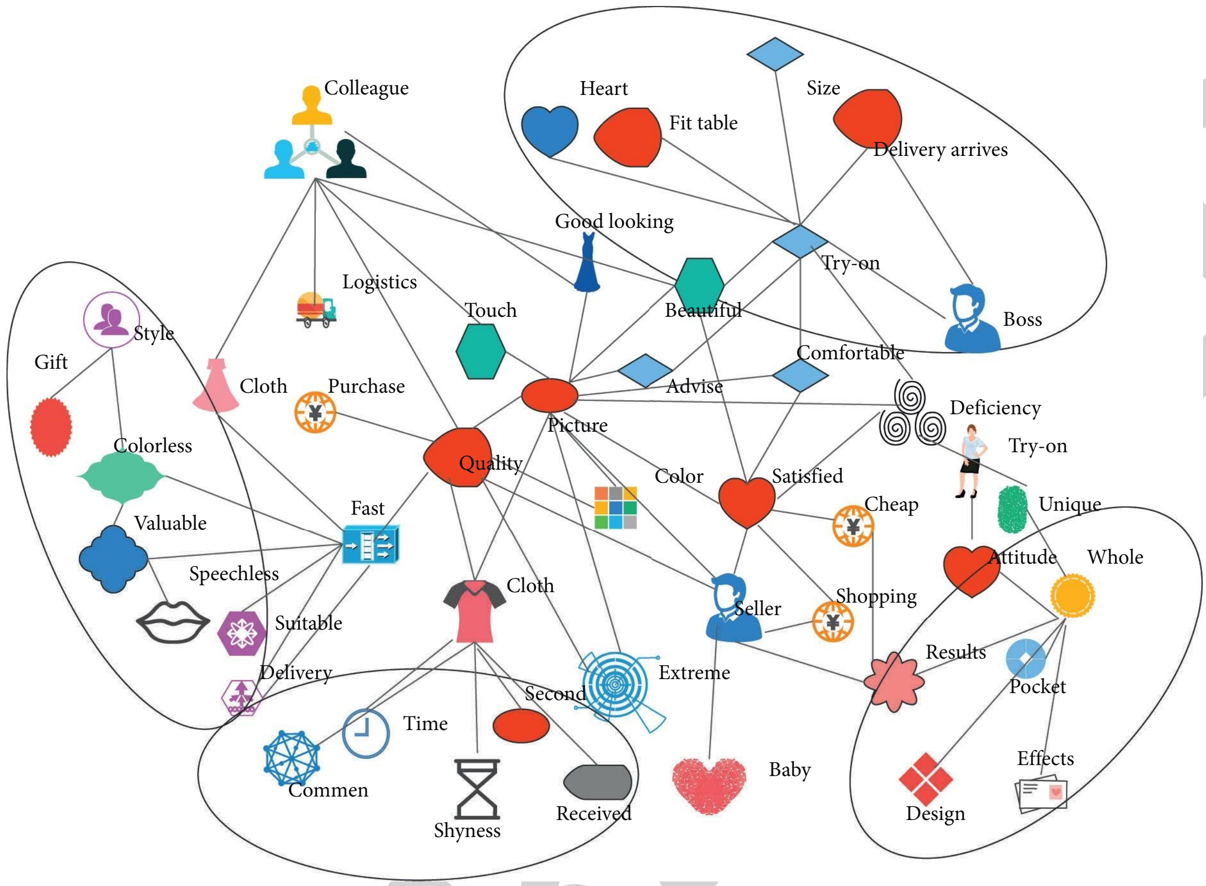

Figure 7: Semantic network structure of online shopping reviews.

Table 1: Semantic analysis and evaluation of personalized recommendation system for online shopping products based on online fast learning through latent factor model.

Number	Semantic analysis	Number	Semantic analysis	Number	Semantic analysis
1	86.96	23	83.62	45	85.15
2	84.03	24	87.66	46	84.04
3	80.71	25	80.90	47	83.28
4	86.75	26	88.71	48	87.42
5	80.73	27	82.51	49	86.72
6	84.38	28	83.72	50	82.09
7	84.93	29	83.88	51	81.88
8	83.27	30	85.79	52	83.83
9	87.83	31	81.88	53	87.68
10	86.83	32	83.20	54	82.08
11	87.35	33	88.54	55	87.51
12	84.81	34	80.31	56	83.60
13	84.61	35	81.32	57	87.44
14	85.30	36	84.57	58	86.93
15	85.77	37	86.41	59	83.89
16	86.01	38	82.61	60	85.96
17	84.17	39	83.36	61	82.75
18	82.20	40	84.78	62	88.93
19	87.22	41	86.28	63	81.30
20	86.64	42	81.39	64	83.64
21	85.34	43	85.45	65	81.91
22	82.00	44	80.34	66	83.52

Table 2: Personalized recommendation effect evaluation of online shopping product personalized recommendation system based on online fast learning through latent factor model.

Number	Recommended effect	Number	Recommended effect	Number	Recommended effect
1	82.54	23	82.04	45	76.27
2	81.76	24	75.10	46	73.11
3	74.84	25	74.64	47	78.54
4	76.57	26	74.14	48	82.10
5	73.07	27	81.16	49	78.41
6	83.63	28	78.09	50	74.92
7	73.27	29	85.75	51	85.55
8	80.51	30	79.39	52	79.96
9	75.64	31	74.06	53	78.81
10	80.81	32	85.37	54	81.82
11	73.40	33	79.69	55	73.04
12	85.57	34	81.94	56	82.11
13	79.20	35	75.73	57	84.15
14	78.61	36	79.79	58	84.10
15	76.67	37	72.22	59	78.75
16	78.84	38	85.06	60	79.88
17	77.51	39	75.88	61	73.42
18	85.09	40	77.36	62	85.63
19	74.50	41	84.74	63	78.22
20	82.19	42	77.84	64	79.22
21	78.87	43	81.46	65	73.84
22	75.77	44	79.82	66	78.19

purchase intention prediction subsystem. The customer purchase intention prediction subsystem mainly uses the knowledge in the knowledge base to complete the customer purchase intention prediction by analyzing the products currently browsed by the customer.

Figure 5 shows the system architecture of the online shopping recommendation system. The framework extracts the user's statistical data and browsing keywords from the database system according to the web page content browsed by the current user. Moreover, according to the current commodity information and historical transaction records, through rule association and data mining, commodity advertisements with the highest degree of correlation are obtained, and then advertisement links are promoted through key positions of web pages.

Based on the existing research model and the analysis of the relationship between the above variables, this article proposes a research model on the influence of online shopping contextual cues on consumers' purchase intention as shown in Figure 6.

On this basis, it is necessary to further explore the basic structure of online shopping review behavior to test the results of text mining. As shown in Figure 7, the online shopping review data are visually mined.

First, the central activity of online shopping reviews is "clothes," which is the center of the entire network, and online shoppers gradually describe prices, details, distribution, packaging, and other links around it. The most closely related keywords are "picture" and "color," indicating that practicality, experience, perception, and social orientation are the core needs in the description of online shopping reviews. Second, with these six core nodes as the source, a small world network is gradually formed, which includes the online shopping review network oriented by loyalty, speed, recommendation, showing off, recognition, sharing, etc., which belongs to the medium demand. Finally, some comments at edge nodes connect all the small networks despite having only a few relationships. Thus, the research results of text mining are verified, and it is found that the network of online shopping reviews presents a three-dimensional hierarchical structure, which reveals the structural evolution of online shopping reviews and the characteristics of goal-oriented behavioral responses.

Based on the above research, the effectiveness of the personalized recommendation system for online shopping products based on the online fast learning through latent factor model proposed in this article is verified. The semantic analysis effect and personalized recommendation effect are evaluated, and the results are obtained as shown in Table 1 and Table 2.

It can be seen from the above research that the online fast learning through latent factor model proposed in this article can play an important role in the personalized recommendation of online shopping products.

5. Conclusion

The unique convenience of online shopping enables consumers to quickly browse products from all over the country and make purchases, and there is no time or place restriction, making shopping easier. The prices of goods purchased online are generally low, giving consumers greater discounts on purchases. Moreover, because there is no sharing of various expenses in the physical store, online shopping is cheaper. Moreover, online shopping product information is more comprehensive, and past consumer evaluations can be searched. In addition, product information is updated quickly, products are easy to find, and consumers can more easily search for product information. Of course, the disadvantages of online shopping are also obvious. Because consumers cannot see the physical products, some product descriptions and pictures do not match the actual ones. In order to improve the personalized recommendation consumption experience of online shopping products, this article combines online fast learning through latent factor model to construct a virtual planning recommendation system for online shopping products. According to the experimental research results, the online fast learning through latent factor model proposed in this article can play an important role in the personalized recommendation of online shopping products.

Data Availability

The labeled dataset that supports the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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