

## Evaluation Model and Influencing Factors of Consumer Satisfaction with E-Commerce Platform



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### ABSTRACT

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*e-commerce platform, consumer satisfaction, evaluation model, artificial neural network*

The boom of online shopping has intensified the competition between e-commerce platforms. To enhance its service quality, every e-commerce website is taking measures to improve shopping experience and consumer satisfaction. However, the existing studies on consumer satisfaction with e-commerce platform fail to fully consider consumer feedbacks, such as sharing, forwarding, and reviewing. Thus, this paper explores the evaluation model and influencing factors of consumer satisfaction with e-commerce platform. Firstly, the behavior features of similar consumers were clustered, and evaluation indices were referred to divide the factors affecting the consumer satisfaction with e-commerce platform into different layers. In addition, a consumer satisfaction evaluation model was constructed based on attention mechanism, and proved effective through experiments.

## 1. INTRODUCTION

With the rapid development of e-commerce related technologies, shopping on e-commerce platform has become a main consumption mode [1, 2]. The intense competition between e-commerce platforms motivates e-commerce websites to enhance their service quality by improving shopping experience and consumer satisfaction [3, 4]. Many e-commerce platforms have simplified the acquisition of the data on consumer behaviors, such as sharing, forwarding, and reviewing. This not only improves the service items and marketing goals of the platforms, but also provides strong data support to the evaluation of consumer satisfaction [5-11].

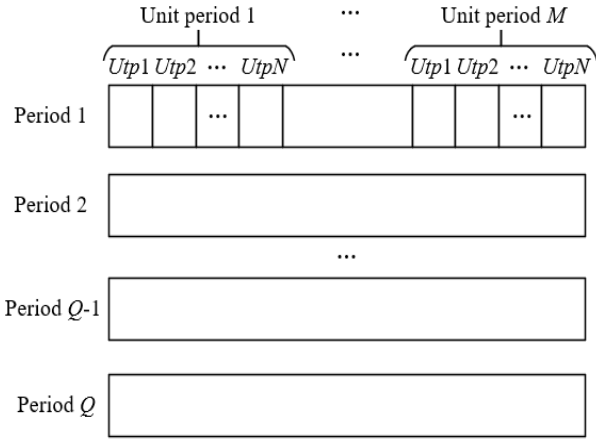
The development of mobile Internet expands the audience of online marketing, and disperses consumer attention [12-16]. Through strength, weakness, opportunity, and threat (SWOT) analysis, Nam and Seong [17] expounded on the correlation between participatory marketing and customer satisfaction, reconstructed a people-oriented path towards participatory marketing, and pointed out the direction of innovative development for this marketing mode. Based on two-factor theory, Liang et al. [18] established a measuring model for consumer satisfaction, and measured the influence of product quality guarantee and product perception over consumer satisfaction. Soltanpour et al. [19] analyzed a massive amount of data on free, anonymous product reviews from online platforms, established the correlations between multi-dimensional factors that affect consumer satisfaction, using a Bayesian network, and set up an accurate and scientific evaluation system based on online review texts. Zhang et al. [20] discussed the reliability and difference of different online product reviews, calculated the utility of online products by Dempster's rule of combination, and evaluated consumer satisfaction through case analysis. Mariani et al. [21] clarified the correlation of consumer satisfaction with six service quality factors of online tourism platform, namely, reliability,

operability, functional completeness, information quality, response speed, security, and experience, identified the positively correlated factors and insignificantly correlated factors, and presented optimization strategies for online tourism platform.

Most studies on consumer satisfaction with e-commerce platform investigate the influencing factors of consumer satisfaction, and innovate the following aspects of the platform: acquisition form of consumer behavior data, interactive interface, and evaluation algorithm, from the perspectives of theory and technology [22-26]. However, few of the proposed e-commerce platforms manage to put consumers at the center, or meet the ideal expectation of consumers, owing to the overlook of platform consumer feedbacks like sharing, forwarding, and reviewing. Thus, this paper explores the evaluation model and influencing factors of consumer satisfaction with e-commerce platform. The main contents of this work are as follows: Section 2 clusters the behavior features of similar consumers; Section 3 relies on evaluation indices to divide the factors affecting the consumer satisfaction with e-commerce platform into different layers, constructs a consumer satisfaction evaluation model based on attention mechanism, and completes index fuzzification and importance calculation. The proposed model was proved effective through experiments.

## 2. EXTRACTION OF CONSUMER BEHAVIOR FEATURES

If two e-commerce platform consumers are strongly correlated, their behavior features will follow similar cyclic change laws. To clearly display the e-commerce consumer behaviors in fixed periods, a two-dimensional (2D) consumer behavior matrix was established (Figure 1), and the behavior features of similar consumers were clustered.



**Figure 1.** Consumer behavior matrix

The time-varying consumer behaviors follow discrete distribution. Therefore, the Gaussian mixture model, which relies on Gaussian probability density function (PDF), applies well to consumer behavior data. The model views a consumption dataset as a collection of  $M$  Gaussian models obeying Gaussian distribution  $A=\{a^{(1)}, a^{(2)}, \dots, a^{(M)}\}$ . The corresponding Gaussian distribution  $M(a; v_j, \Sigma_j)$  is the cluster center of each class of consumer behavior features. Let  $l$  be the number of Gaussian mixture models;  $\psi_j$  be the weight coefficient of each model;  $\xi_j$  and  $\lambda_j$  be the mean and covariance of Gaussian distribution features, respectively. For each Gaussian model, there is:

$$A \sim \sum_{j=1}^l \psi_j M(\lambda_j, \xi_j) \quad (1)$$

Let  $\omega$  be the set of parameter vectors. The composite Gaussian mixture model can be expressed as:

$$GV(a, \omega) = \sum_{j=1}^l \psi_j g(a; \lambda_j, \xi_j) \quad (2)$$

Let  $VB$  be the dimension of observations. Then, we have:

$$g(a; \lambda_j, \xi_j) = \frac{1}{\sqrt{(2\pi)^{VB} |\xi_j|}} \exp\left[-\frac{1}{2}(a - \lambda_j)^T \xi_j^{-1} (a - \lambda_j)\right] \quad (3)$$

To acquire the hidden variables from consumer behavior data, parameters  $\psi$ ,  $\lambda$  and  $\xi$  are calculated by the expectation-maximization (EM) clustering algorithm, which is a two-step iterative algorithm. The first step is to compute the posterior probability  $\phi^{(i)}$  of parameter  $c^{(i)}$ , using the Bayesian formula:

$$\begin{aligned} \phi^{(i)} &= GV(c^{(i)} = j | a^{(i)}; \psi, \lambda, \xi) = \frac{GV(a^{(i)} | c^{(i)} = j) GV(c^{(i)} = j)}{\sum_{k=1}^l GV(a^{(i)} | c^{(i)} = k) GV(c^{(i)} = k)} \\ &= \frac{GV(a^{(i)} | c^{(i)} = j, \lambda, \xi) GV(c^{(i)} = j; \psi)}{\sum_{k=1}^l GV(a^{(i)} | c^{(i)} = k, \lambda, \xi) GV(c^{(i)} = k; \psi)} \end{aligned} \quad (4)$$

Formula (4) shows  $\phi^{(i)}$ , which characterizes the model estimation of  $c^{(i)}$ , can be derived from parameter  $a^{(i)}$  and current parameters  $\psi$ ,  $\lambda$  and  $\xi$ . Next, the probability of

consumer behavior sample  $i$  belonging to feature class  $j$  is denoted as  $\phi_j^{(i)}$ . The current parameters  $\psi$ ,  $\lambda$  and  $\xi$  can be updated by:

$$\psi_j = \frac{1}{M} \sum_{i=1}^M \phi_j^{(i)}, \lambda_j = \frac{\sum_{i=1}^M \phi_j^{(i)} a^{(i)}}{\sum_{i=1}^M \phi_j^{(i)}}, \xi_j = \frac{\sum_{i=1}^M \phi_j^{(i)} (a^{(i)} - \lambda_j)(a^{(i)} - \lambda_j)^T}{\sum_{i=1}^M \phi_j^{(i)}} \quad (5)$$

The above steps are repeated to update parameter  $\omega$  continuously until the model converges.

To clarify the degree of consumer satisfaction, it is necessary to distinguish between e-commerce platform consumers by activity. In this paper, the consumption behavior modes and features are evaluated by two indices: bookmarking/reviewing (BR) frequency and the number of days for BR records.

Suppose the historical consumption data span across  $Q$  periods. Let  $\varepsilon_{vq}$  be the number of BR by consumer  $v$  in period  $q$ . Based on the BR records of 4,000 consumers in the e-commerce platform consumption dataset, the BR frequency  $NCM_v$  by consumer  $v$  in a fixed period can be calculated by:

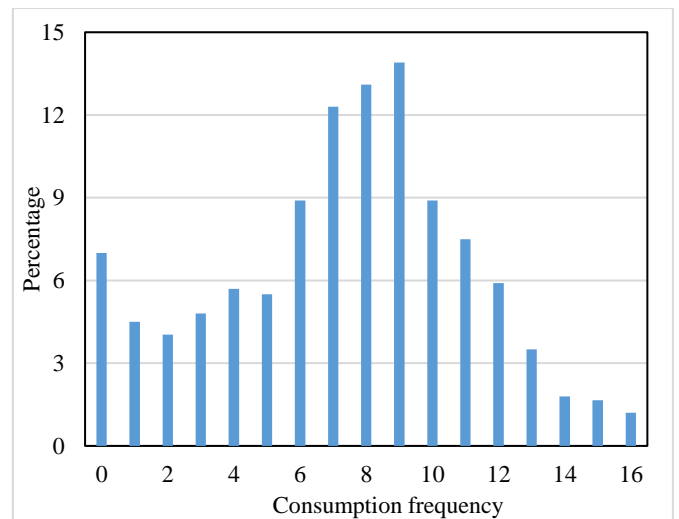
$$NCM_v = \frac{\sum_{w=1}^Q \varepsilon_{vq}}{Q} \quad (6)$$

Out of the  $Q$  periods, consumer  $v$  has BR record(s) in  $CNW_v$  periods:

$$CNW_v = \sum_{q=1}^Q F(q) \quad (7)$$

where,  $F(q)$  is a binary function reflecting whether consumer  $v$  has BR record(s) in period  $q$ . If he/she has BR record(s),  $F(q)=1$ ; if he/she does not have BR record(s),  $F(q)=0$ .

Based on the calculated BR frequency and the number of days for BR records, the e-commerce platform consumers can be preliminarily classified by activity. Figure 2 displays the distribution of consumption frequency derived from the BR frequency.



**Figure 2.** Distribution of consumption frequency

The consumption frequency of e-commerce platform consumers is generally affected by internal and external

factors, such as living habits, preferences, and holidays. For moderately active consumers, their consumption frequency changes cyclically in a fixed period, and their activity differ between holidays and non-holidays. Based on BR frequency and the number of days for BR records, this paper divides consumers to four classes by activity: weakly active, moderately active 1, moderately active 2, and strongly active (Figure 3).

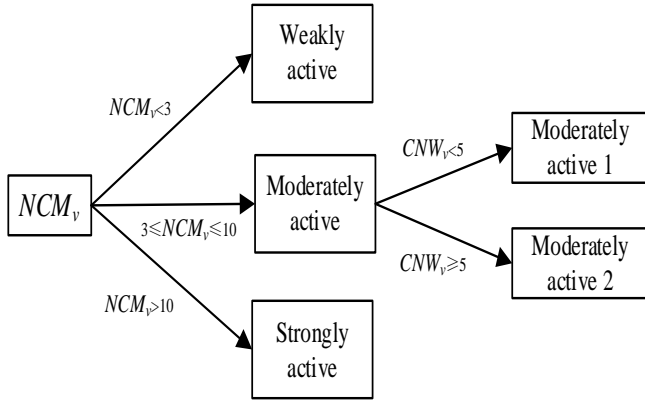


Figure 3. Activity-based consumer classification rules

### 3. ATTENTION-BASED CONSUMER SATISFACTION EVALUATION MODEL

#### 3.1 Model construction

Long short-term memory (LSTM) network is a special structure extended from recurrent neural network (RNN). The storage unit of LSTM network consists of an input gate, an output gate, and a forget gate. The interaction between the three gates controls the network operation. Under the action of activation functions, the three gates generate numbers between 0 and 1 to control their opening and close, and further determine the retaining or removal of historical information. The formula of the forget gate can be given by:

$$YG_{\varepsilon} = \Gamma(Q_g \cdot [F_{\varepsilon-1}, A_{\varepsilon}] + r_g) \quad (8)$$

The formula of the input gate can be given by:

$$GA_{\varepsilon} = \Gamma(Q_i \cdot [F_{\varepsilon-1}, A_{\varepsilon}] + r_i) \quad (9)$$

The current state  $EUS_{\varepsilon}$  of the input unit can be calculated by:

$$EUS_{\varepsilon} = YG_{\varepsilon} \times EUS_{\varepsilon-1} + GA_{\varepsilon} \times EUS_{\varepsilon}^* \quad (10)$$

where,  $EUS_{\varepsilon}^*$  is the current memory:

$$EUS_{\varepsilon}^* = \tanh(Q_{EUS} \cdot [F_{\varepsilon-1}, A_{\varepsilon}] + r_{EUS}) \quad (11)$$

Formulas (10) and (11) show that the current memory  $EUS_{\varepsilon}^*$  combined with the input unit state  $EUS_{\varepsilon-1}$  at the previous moment is the new input unit state  $EUS_{\varepsilon}$ . The formula of the output gate can be given by:

$$D_{\varepsilon} = \Gamma(Q_D \cdot [F_{\varepsilon-1}, A_{\varepsilon}] + r_D) \quad (12)$$

$$F_{\varepsilon} = D_{\varepsilon} \times \tanh(EUS_{\varepsilon}) \quad (13)$$

The consumption behavior data of each e-commerce platform consumer contain two implicit rules: First, the consumption is driven by consumer satisfaction; Second, consumption records demonstrate different kinds of consumer satisfaction. Based on these two rules, this paper constructs an LSTM-based mining model for consumer satisfaction. In the model, the satisfaction state comes from the consumer behavior sequence. In addition, the attention mechanism was introduced to the LSTM network to extract the satisfaction information from consumers in different satisfaction states, thereby screening the satisfaction states outputted by the LSTM network.

In the attention layer, the satisfaction classes implied in a consumer behavior sequence are denoted as  $x, y, z, \dots$ . The consumer behavior sequence corresponding to each satisfaction state can be expressed as  $[x_1, x_2, \dots, x_m] \sim x, [y_1, y_2, \dots, y_m] \sim y, [z_1, z_2, \dots, z_m] \sim z, \dots$ . Therefore, this paper chooses  $[x_1, y_1, z_1, x_2, y_2, z_2, \dots]$  to depict the consumer behavior sequences of e-commerce platform consumers, which obey discrete distribution. In this way, the consumer behavior sequences of multiple satisfaction states can be combined into a hybrid consumer behavior sequence.

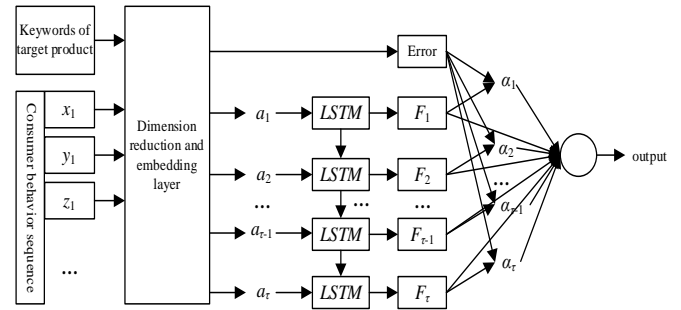


Figure 4. Attention-based consumer satisfaction evaluation model

Figure 4 illustrates our attention-based consumer satisfaction evaluation model, which comprises of an input layer of consumer behavior data, a dimension reduction and embedding layer, a LSTM network layer, an attention layer, and an output layer of satisfaction evaluation result.

#### 3.2 Evaluation index system (EIS) construction and fuzzification

The factors affecting consumer satisfaction with e-commerce platform were divided into multiple layers according to evaluation indices. The hierarchical EIS contains 20 secondary indices and 5 primary indices.

Layer 1 (Goal layer):

$CS = \{\text{overall consumer satisfaction with e-commerce platform}\}$

Layer 2 (Primary indices):

$CS = \{CS_1, CS_2, CS_3, CS_4, CS_5\} = \{\text{personalized recommendation contents, service quality, system response, functional completeness, utility}\}$

Layer 3 (Secondary indices):

$CS_1 = \{CS_{11}, CS_{12}, CS_{13}, CS_{14}, CS_{15}\} = \{\text{content diversity, content attractiveness, content authenticity, content recommendation accuracy, content display comprehensiveness}\};$

$CS_2=\{CS_{21}, CS_{22}, CS_{23}, CS_{24}\}=\{\text{consulting response speed, after-sales mode, after-sales personnel service attitude, return speed}\};$

$CS_3=\{CS_{31}, CS_{32}\}=\{\text{information transfer capability, information transfer mode}\};$

$CS_4=\{CS_{41}, CS_{42}, CS_{43}, CS_{44}, CS_{45}, CS_{46}\}=\{\text{activity page friendliness, operability, query performance, ease of information storage, accessibility, smoothness of complaint channel}\};$

$CS_5=\{CS_{51}, CS_{52}, CS_{53}\}=\{\text{system operation efficiency, system resource expansibility, system resource occupation}\}$

In the EIS of consumer satisfaction with e-commerce platform, the correlation intensities between overall satisfaction and primary indices are denoted as  $S^{(1)}_i(i=1, 2, \dots, n)$ ; the importance of primary indices is denoted as  $\varphi^{(1)}_i(i=1, 2, \dots, n)$ ; the autocorrelation intensities between primary indices is denoted as  $s_{jn}(j=1, 2, \dots, n)$ ; the correlation intensity between primary index  $i$  and secondary index  $j$  is denoted as  $S_{ij}(i=1, 2, \dots, n; j=1, 2, \dots, m)$ ; the importance of secondary indices is denoted as  $\varphi^{(2)}_j(j=1, 2, \dots, m)$ ; the satisfaction indices of primary indices are denoted as  $SA^{(1)}_i(i=1, 2, \dots, n)$ ; the consumer satisfaction evaluated by secondary indices is denoted as  $ER_j(j=1, 2, \dots, m)$ .

After normalization, the correlation intensity  $S'_{ij}$  between evaluation indices can be calculated by:

$$S'_{ij} = \frac{\sum_{l=1}^m S_{ik} S_{kj}}{\sum_{j=1}^m \sum_{l=1}^m S_{il} S_{lj}}, (i=1,2,\dots,n; j=1,2,\dots,m) \sum_j S'_{ij} = 1 \quad (14)$$

Let  $S^*_{il}$  be the fuzzy correlation between an index and a factor affecting consumer satisfaction;  $s^*_{lj}$  be the fuzzy autocorrelation between factors affecting consumer satisfaction. Then, the fuzzy relationship between  $S^*_{il}$  and  $s^*_{lj}$  can be expressed as:

$$S^*_{ij} = \frac{\sum_{l=1}^m S^*_{il} \circ s^*_{lj}}{\sum_{j=1}^m \sum_{l=1}^m S^*_{il} \circ s^*_{lj}}, (i=1,2,\dots,n; j=1,2,\dots,m) \quad (15)$$

where,  $S^*_{il}=\{(S_{il}, \lambda_{s_{il}}(S_{il}))|S_{il} \in S\}$ ;  $s^*_{lj}=\{(s_{lj}, \lambda_{s_{lj}}(s_{lj}))|s_{lj} \in s\}$  ( $S_{il}$  and  $s_{lj} \in [0, 1]$ ). Let  $S$  denote the set of correlations between indices and influencing factors, and  $s$  denote the set of autocorrelations between influencing factors. To determine the membership function of  $S^*_{ij}$ , the  $\alpha$ -cut set of  $S^*_{il}$  is described as a discrete interval based on Zadeh's series expansion:

$$(S_{il})_\alpha = \left[ \min_{S_{il}} \{S_{il} \in S | \lambda_{S_{il}}(S_{il}) \geq \alpha\}, \max_{S_{il}} \{S_{il} \in S | \lambda_{S_{il}}(S_{il}) \geq \alpha\} \right] = [(S_{il})_\alpha^K, (S_{il})_\alpha^V] \quad (16)$$

The discrete interval for the  $\alpha$ -cut set of  $S^*_{il}$  can be given by:

$$(s_{il})_\beta = \left[ \min_{s_{il}} \{s_{il} \in s | \lambda_{s_{il}}(s_{il}) \geq \beta\}, \max_{s_{il}} \{s_{il} \in s | \lambda_{s_{il}}(s_{il}) \geq \beta\} \right] = [(s_{il})_\beta^K, (s_{il})_\beta^V] \quad (17)$$

Let  $\lambda_{S^*_{il}}(S_{il})$  and  $\lambda_{s^*_{lj}}(s_{lj})$  be the membership functions of  $S_{il}$  and  $s_{lj}$ , respectively. By Zadeh's series expansion, the membership function of  $S'_{ij}$  can be derived as:

$$\lambda_{S'_{ij}}(S'_{ij}) = \sup_{S_{ij}} \min_{s_{ij}} \left\{ \lambda_{S_{il}}(S_{il}), \lambda_{s_{lj}}(s_{lj}), \forall l, j \mid S'_{ij} = \frac{\sum_{l=1}^m S_{il} S_{lj}}{\sum_{j=1}^m \sum_{l=1}^m S_{il} S_{lj}} \right\} \quad (18)$$

The membership function of  $S'_{ij}$  can be deduced from the  $\alpha$ -cut set of  $S'_{ij}$ . The upper bound  $(S'_{ij})^V_\alpha$  and lower bound  $(S'_{ij})^K_\alpha$  of the  $\alpha$ -cut set of  $S'_{ij}$  can be solved by:

$$S'_{ij} = \frac{\sum_{l=1}^m S_{il} S_{lj}}{\sum_{j=1}^m \sum_{l=1}^m S_{il} S_{lj}} = \frac{\sum_{l=1}^m S_{il} S_{lj}}{\sum_{j=1}^m \sum_{l=1}^m S_{il} S_{lj} + \sum_{l=1}^m S_{il} S_{lj}} \quad (19)$$

where,  $S_{il}$  and  $s_{lj}$  satisfy inequality  $0 \leq (S_{il})^K_\alpha \leq S_{il} \leq (S_{il})^V_\alpha \leq 1$ , and  $0 \leq (s_{lj})^K_\alpha \leq s_{lj} \leq (s_{lj})^V_\alpha \leq 1$ . Suppose

$$\chi = \sum_{l=1}^m S_{il} S_{lj}, \delta = \sum_{k=1}^m \sum_{l=1}^m S_{il} S_{lj} \quad (20)$$

Then, formula (19) can be expressed as:

$$g(\chi) = \frac{\chi}{\delta + \chi} \quad (21)$$

The first-order derivative of  $g(\chi)$  satisfies:

$$g'(\chi) = \frac{\chi}{(\delta + \chi)^2} \geq 0 \quad (22)$$

Since  $g'(\chi) > 0$ ,  $g(\chi)$  is an increasing function, and  $\chi$  satisfies:

$$\sum_l (S_{il})^K_\alpha (s_{lj})^K_\alpha \leq \chi \leq \sum_l (S_{il})^V_\alpha (s_{lj})^V_\alpha \quad (23)$$

Thus, the minimum of  $g(\chi)$  can be obtained:

$$\min g(\chi) = \frac{\sum_{l=1}^m (S_{il})^K_\alpha (s_{lj})^K_\alpha}{\delta + \sum_{l=1}^m (S_{il})^K_\alpha (s_{lj})^K_\alpha} \quad (24)$$

$$\max g(\chi) = \frac{\sum_{l=1}^m (S_{il})^V_\alpha (s_{lj})^V_\alpha}{\delta + \sum_{l=1}^m (S_{il})^V_\alpha (s_{lj})^V_\alpha} \quad (25)$$

The upper bound  $(S'_{ij})^V_\alpha$  and lower bound  $(S'_{ij})^K_\alpha$  of the  $\alpha$ -cut set of  $S'_{ij}$  can be respectively expressed as:

$$(S'_{ij})_{\alpha}^K = \min g(\chi) = \frac{\sum_{l=1}^m (S_{il})_{\alpha}^K (s_{lj})_{\alpha}^K}{\sum_{k=1}^m \sum_{l=1}^m (S_{il})_{\alpha}^K (s_{lj})_{\alpha}^K + \sum_{l=1}^m (S_{il})_{\alpha}^K (s_{lj})_{\alpha}^K} \quad (26)$$

$$(S'_{ij})_{\alpha}^V = \max g(\chi) = \frac{\sum_{l=1}^m (S_{il})_{\alpha}^V (s_{lj})_{\alpha}^V}{\sum_{k=1}^m \sum_{l=1}^m (S_{il})_{\alpha}^K (s_{lj})_{\alpha}^K + \sum_{l=1}^m (S_{il})_{\alpha}^V (r_{lj})_{\alpha}^V} \quad (27)$$

Based on the upper bound  $(S'_{ij})_{\alpha}^V$  and lower bound  $(S'_{ij})_{\alpha}^K$  of the  $\alpha$ -cut set of  $S'_{ij}$ , it is possible to evaluate the importance of each index in the EIS.

### 3.3 Importance calculation

The evaluation model for consumer satisfaction with e-commerce platform can be fuzzy normalized by formulas (26) and (27). After fuzzy normalization of  $S^{(1)}_i$  and  $s_{in}$  ( $i=1, 2, n$ ), the upper bound  $(S'_{ij})_{\alpha}^V$  and lower bound  $(S'_{ij})_{\alpha}^K$  of the  $\alpha$ -cut set of  $S'_{ij}$  can be calculated. If  $\alpha=1$ , there exists:

$$\sum_{i=1}^n (S'_i)_{\alpha}^K = \sum_{i=1}^n (S'_i)_{\alpha}^V = 1 \quad (28)$$

The importance of primary indices can be calculated by:

$$\phi_i^{*(1)} = (S'_i)_{\alpha}^K = (S'_i)_{\alpha}^V, \alpha = 1 \text{ and } \sum_{i=1}^n \phi_i^{*(1)} = 1 \quad (29)$$

If  $\alpha \neq 1$ , there exists:

$$(\phi_i^{*(1)})_{\alpha} = [(S'_i)_{\alpha}^K, (S'_i)_{\alpha}^V], i = 1, 2, \dots, n \quad (30)$$

In the evaluation model for consumer satisfaction with e-commerce platform, the importance of secondary indices is jointly determined by the fuzzy normalized relationship between primary and secondary indices, and the importance of primary indices  $\phi_i^{*(1)}$  ( $i=1, 2, \dots, n$ ). Let  $S'_{ij}$  be the fuzzy normalized relationship between primary index  $i$  and secondary index  $j$ . Following fuzzy quality function deployment (FQFD), the fuzzy coefficient  $Q^{*(2)}_j$  ( $j=1, 2, \dots, m$ ) of secondary index  $j$  can be calculated by:

$$Q_j^{*(2)} = \sum_{i=1}^n \phi_i^{*(1)} \circ S'_{ij} \quad (31)$$

Under a certain level of  $\alpha$ , the upper and lower bounds of the  $\alpha$ -cut set of  $Q^{*(2)}_j$  can be expressed as:

$$\begin{aligned} (Q_j^{*(2)})_{\alpha} &= \left[ (Q_j^{*(2)})_{\alpha}^K, (Q_j^{*(2)})_{\alpha}^V \right] \\ &= \left[ \sum_{i=1}^n \phi_i^{*(1)} \circ (S'_{ij})_{\alpha}^K, \sum_{i=1}^n \phi_i^{*(1)} \circ (S'_{ij})_{\alpha}^V \right] \end{aligned} \quad (32)$$

where,  $Q^{*(2)}_j$  measures the degree of influence of primary index  $i$  on secondary index  $j$ , i.e., the importance of the secondary index relative to its superior primary index.

### 3.4 Consumer satisfaction index

In the FQFD model of consumer satisfaction with e-commerce platform, the first step is to compute the mean fuzzy triangular number based on the evaluation results on each row in the secondary index judgement matrix:

$$ER_j^* = \frac{\sum_{i=1}^n (x_{ij}, y_{ij}, z_{ij})}{n} = \left( \sum_{i=1}^n \frac{x_{ij}}{n}, \sum_{i=1}^n \frac{y_{ij}}{n}, \sum_{i=1}^n \frac{z_{ij}}{n} \right) \quad (33)$$

Next, the mean fuzzy triangular number  $ER_j^*$  is cross-multiplied with the fuzzy coefficient  $Q^{*(2)}_j$  of secondary index importance at different levels of  $\alpha$  to obtain the consumer satisfaction  $SA^{*(1)}_i$  ( $i=1, 2, \dots, n$ ) with primary indices at different levels of  $\alpha$ :

$$\begin{aligned} (SA_i^{*(1)})_{\alpha} &= \sum_{j=1}^m ER_{ij}^* \circ (Q_j^{*(2)})_{\alpha} \\ &= \left[ \sum_{j=1}^m (ER_{ij}^*)_{\alpha}^K \circ (Q_j^{*(2)})_{\alpha}^K, \sum_{j=1}^m (ER_{ij}^*)_{\alpha}^V \circ (Q_j^{*(2)})_{\alpha}^V \right] \end{aligned} \quad (34)$$

The mean fuzzy triangular number  $ER_j^*$  can be written in the form of an  $\alpha$ -cut set:

$$\begin{aligned} ER_{ij}^* &= \left[ (ER_{ij}^*)_{\beta}^K, (ER_{ij}^*)_{\beta}^V \right] \\ &= \left[ f_{ij} + (r_{ij} - f_{ij})\beta, SA_{ij} - (SA_{ij} - f_{ij})\beta \right], \forall \beta \in [0, 1] \end{aligned} \quad (35)$$

After that, the  $SA^{*(1)}_i$  is multiplied with the importance  $(\phi_i^{*(1)})_{\alpha}$  ( $i=1, 2, \dots, n$ ) of a primary index at the corresponding level of  $\alpha$ . The products are added up into the overall consumer satisfaction  $(TS)_{\alpha}$  at different levels of  $\alpha$ :

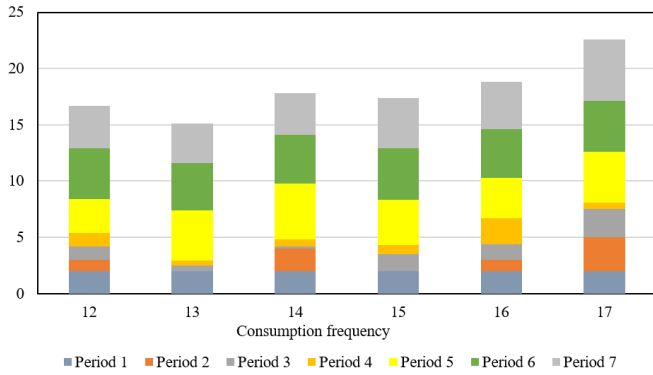
$$(TS)_{\alpha} = \sum_{i=1}^n (\phi_i^{*(1)})_{\alpha} \otimes (SA_i^{*(1)})_{\alpha}, i = 1, 2, \dots, n \quad (36)$$

## 4. EXPERIMENTS AND RESULTS ANALYSIS

By the EM clustering method of Gaussian mixture model, this paper extracts the BR records of active consumers on e-commerce platform from November to December, 2020. The consumer behavior records in each unit period were expressed as a  $G \times H$ -dimensional vector, where  $G$  is the number of days in the fixed period, and  $H$  is the number of labels of the product. Then, the consumer behavior matrix was clustered. The periods when consumers follow the same consumption mode were clustered into one class, aiming to effectively differentiate between the behavior features of consumers on different levels of activity. Figure 5 shows the clustering results of consumer behaviors.

As shown in Figure 5, the BR frequencies were close within each class of behavior features, and dispersed between different classes. The behavior features extracted from

holidays differed from those extracted from non-holidays: the consumption activity on holidays was higher than that on non-holidays.

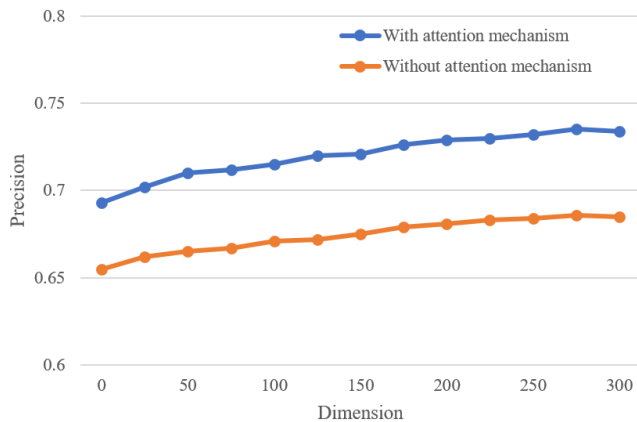


**Figure 5.** Clustering results of consumer behaviors

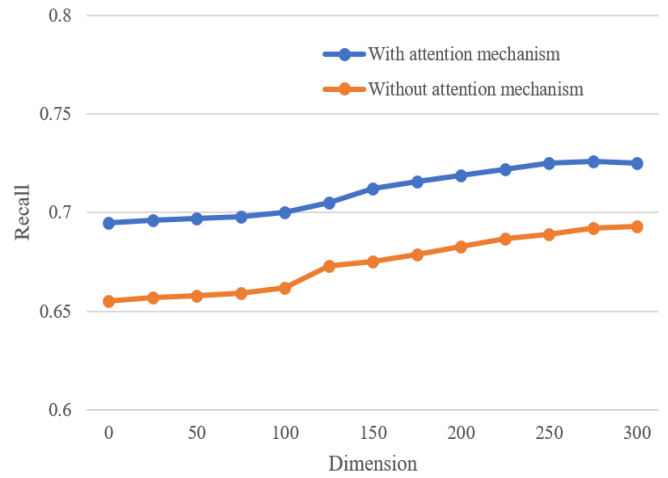
Our evaluation model for consumer satisfaction with e-commerce platform was realized based on machine learning library PyTorch. The batch size and learning rate of the model were set to 32 and 0.01, respectively. The optimal solution was searched for by the adaptive moment estimation algorithm. The e-commerce platform consumption dataset involves 25,145 products. The embedding dimension was set to 13 values between 0 and 320. Besides, the output of the embedding layer was imported to RNN and LSTM network, respectively, for network training. Figures 6-8 report the precisions, recalls, and F1 scores of evaluation models with different embedding dimensions, respectively.

As shown in Figures 6-8, the evaluation models with or without attention mechanism witnessed the improvement of evaluation effect and performance with the growth of the embedding dimension. Judging by any of the three metrics (precision, recall, and F1 score), the attention-based prediction model was better than the original model.

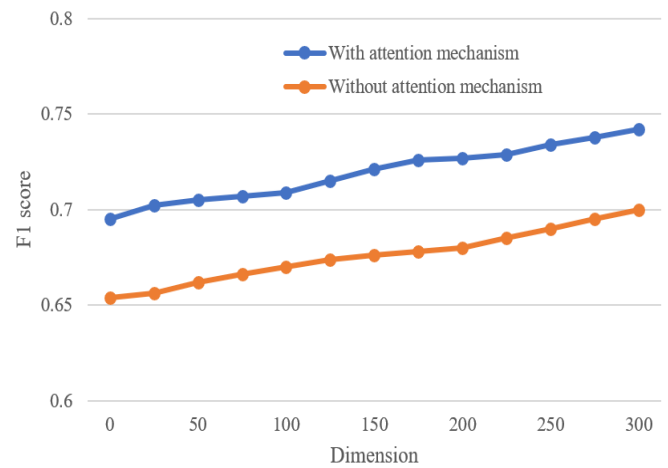
Figure 9 compares the prediction performance metrics of different evaluation models. To acquire the accurate features of consumption behaviors, our model was founded on LSTM network, which is a special structure of RNN, and the attention mechanism. As shown in Figure 9, our model achieved better prediction of consumer satisfaction than traditional RNN, traditional LSTM, and the RNN with attention mechanism. The prediction accuracy of our model was as high as 84.5%.



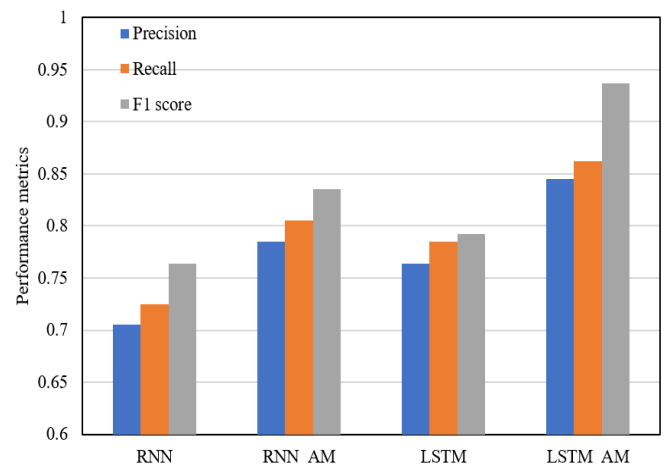
**Figure 6.** Precisions of evaluation models with different embedding dimensions



**Figure 7.** Recalls of evaluation models with different embedding dimensions



**Figure 8.** F1 scores of evaluation models with different embedding dimensions



**Figure 9.** Prediction performance of different evaluation models

The fuzzy values of consumer satisfaction indices could be calculated for primary indices (Table 1). The consumer satisfaction indices in Table 1 were imported to our model, and the fuzzy overall consumer satisfaction could be derived for e-commerce platform consumers at each level of  $\alpha$ , using formula (36). The calculation results are shown in Table 2.

**Table 1.** Consumer satisfaction indices of primary indices

Secondary indices and their importance		Primary indices				
		CS <sub>1</sub>	CS <sub>2</sub>	CS <sub>3</sub>	CS <sub>4</sub>	CS <sub>5</sub>
CS <sub>11</sub>	0.0632	0.6724				
CS <sub>12</sub>	0.0854	0.6821				
CS <sub>13</sub>	0.0215	0.7396				
CS <sub>14</sub>	0.0236	0.6142				
CS <sub>15</sub>	0.0973	0.6789				
CS <sub>21</sub>	0.1571		0.6176			
CS <sub>22</sub>	0.3678		0.6531			
CS <sub>23</sub>	0.1267		0.6478			
CS <sub>24</sub>	0.0325		0.6392			
CS <sub>31</sub>	0.0408			0.7131		
CS <sub>32</sub>	0.0362			0.6042		
CS <sub>41</sub>	0.0375				0.5328	
CS <sub>42</sub>	0.0329				0.6492	
CS <sub>43</sub>	0.0571				0.6747	
CS <sub>44</sub>	0.0523				0.6375	
CS <sub>45</sub>	0.0465				0.7592	
CS <sub>46</sub>	0.0674				0.6508	
CS <sub>51</sub>	0.0238					0.6376
CS <sub>52</sub>	0.0842					0.6542
CS <sub>53</sub>	0.0542					0.5987
Satisfaction with primary indices		0.1723	0.1894	0.1676	0.1835	0.1842

**Table 2.** Overall satisfaction TS of e-commerce platform consumers

Primary indices	$\alpha=1$					$(TS)_{\alpha=1}$
	CS <sub>1</sub>	CS <sub>2</sub>	CS <sub>3</sub>	CS <sub>4</sub>	CS <sub>5</sub>	
$\phi^{(1)}_i$	0.213	0.267	0.219	0.245	0.245	0.172
$SA^{(1)}_i$	0.184	0.167	0.136	0.143	0.143	
	$\alpha=0.5$					$(TS)_{\alpha=0.5}$
$\phi^{(1)}_i$	[0.236, 0.348]	[0.213, 0.387]	[0.183, 0.375]	[0.127, 0.236]	[0.143, 0.222]	[0.076, 0.403]
$SA^{(1)}_i$	[0.112, 0.379]	[0.103, 0.273]	[0.067, 0.273]	[0.085, 0.386]	[0.093, 0.374]	
	$\alpha=0$					$(TS)_{\alpha=0}$
$\phi^{(1)}_i$	[0.217, 0.437]	[0.194, 0.376]	[0.063, 0.328]	[0.136, 0.396]	[0.117, 0.385]	[0.037, 0.796]
$SA^{(1)}_i$	[0.051, 0.573]	[0.052, 0.423]	[0.037, 0.419]	[0.041, 0.575]	[0.094, 0.612]	

**5. CONCLUSIONS**

This paper investigates the evaluation model and influencing factors of consumer satisfaction with e-commerce platform. Specifically, the behavior features of similar consumers were clustered, the evaluation indices were referred to divide the factors affecting the consumer satisfaction with e-commerce platform into different layers, and a consumer satisfaction evaluation model was constructed based on attention mechanism. Then, experiments were carried out to cluster consumer behaviors. The results verify the difference between feature classes of consumer behaviors on e-commerce platform. In addition, the precisions, recalls, and F1 scores of evaluation models with different embedding dimensions were compared, and the prediction performance metrics of these models were contrasted. The comparison demonstrates the superiority of our model in the prediction of consumer satisfaction with e-commerce platform. Finally, the fuzzy overall satisfaction of e-commerce platform consumers was obtained at each level of  $\alpha$ .

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