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Influence of online E-commerce interaction on consumer satisfaction based on big data algorithm

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ABSTRACT

With the rapid development of the times, people have entered the era of intelligence, and the application of big data algorithms is becoming increasingly widespread. The satisfaction of consumers in online shopping is closely related to communication and interaction during shopping. Based on this, this article studies the impact of online e-commerce interaction on consumer satisfaction based on big data algorithms. This article introduces the mediating variable of consumer satisfaction from the perspective of interaction, constructs a model between interaction and trust, and studies the internal impact mechanism of online interaction on consumer satisfaction in online shopping. This article takes the JD interactive shopping platform as the research object, and analyzes and explores the target consumer satisfaction of the women's clothing interactive shopping platform. Analyzed the impact of interaction on merchant qualifications and service satisfaction evaluations, store size, and logistics of purchased goods. The research results indicate that the normalization coefficients of the H1a and H1b pathways are 0.131 and 0.118, respectively, which are slightly smaller, indicating that the impact of perceived risk on consumer satisfaction is not significant. Meanwhile, the CR in H1 is a positive number and the direction of influence is positive, which is contrary to the assumption. Therefore, it is necessary to calibrate the initial model. After correction, the GFI value is 0.816, AGFI value is 0.825, RMSEA value is 0.042, TFI value is 0.930, CFI value is 0.955, PGFI value is 0.718, and PNFI value is 0.810. The degree is within an acceptable range. Therefore, when implementing interactive shopping, e-commerce companies need to create a good shopping environment for the implementation of interactive activities between sellers and customers. The impact of online e-commerce interaction based on big data algorithms on consumer satisfaction is a hot topic. Personalized recommendations can improve consumer satisfaction and loyalty, but data privacy and security issues are also receiving increasing attention. In addition, it is also necessary to consider the fairness and bias issues of the algorithm, as well as the transparency issues of data analysis and decision-making. On the premise of ensuring data privacy and security, it is necessary to improve the fairness and transparency of algorithms to improve consumer satisfaction and trust, and achieve sustainable development.

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1. Introduction

With the popularization of the Internet, e-commerce has become an indispensable part of people's daily lives. Nowadays, more and more consumers are choosing to shop online, which provides more business opportunities for e-commerce enterprises and also brings consumers more choices. However, with the intensification of competition, the needs and psychology of consumers are constantly changing. How to improve consumer satisfaction has become a problem that e-commerce enterprises must solve. In this context, the impact of online e-commerce interaction based on big data algorithms on consumer satisfaction has become a highly focused research direction. By analyzing big data such as consumer shopping behavior, interaction data, and feedback information, e-commerce enterprises can better understand consumer needs and psychology, and make personalized recommendations and services based on this information, improving consumer shopping experience and satisfaction. At the same time, big data algorithms can also help e-commerce enterprises better understand consumer preferences and trends, thereby adjusting product and service strategies in a timely manner, and improving the quality and competitiveness of products and services. In addition, big data algorithms can also help e-commerce enterprises better manage their supply chain and inventory, improve operational efficiency and reduce costs, thereby providing consumers with higher quality products and services. Therefore, the impact of online e-commerce interaction based on big data algorithms on consumer satisfaction has important background significance. By analyzing big data, e-commerce enterprises can better understand consumer needs and psychology, provide personalized recommendations and services, thereby improving consumer satisfaction and loyalty, enhancing competitiveness, and achieving sustainable development.

In the Grobovic M study, online interaction is divided into. Interpersonal interaction and human-computer interaction. Interpersonal interaction refers to the process of human-to-human communication between users using computer media and other users; human-computer interaction refers to the process of users accessing computer-stored information [1]. Sheng B divides online interaction into content interaction and interpersonal interaction from the perspective of journalism [2]. Based on the perspective of online interaction communication process, Ma X divides online interaction into three types: human-computer interaction, social interaction, and information interaction [3]. When Tang Z studies the online interaction of virtual communities, firstly, it will segment the members of the virtual community by market segmentation, and then analyze the communication tendencies and purposes of the members in different groups, and finally divide the online interaction into four modes according to the purpose of interaction: information mode, relationship mode. Entertainment mode and conversion mode [4]. The e-commerce market continued to grow. It is so popular because more and more people are connected to the Internet. However, not all online electronic stores can be proud of their conversion rate. Ingaldi Manuela decided to use two methods to evaluate the customer satisfaction of the selected electronic store. According to these two methods, they can complement each other [5]. The recent emergence of e-commerce has brought a paradigm shift to the global market. Costa Joana has two goals: first, collect relevant data on the adoption of e-commerce by small and medium-sized enterprises through systematic literature review including 32 index articles. Secondly, it provides quantitative and qualitative analysis to determine the strategic options and guidelines for achieving a smooth digital transformation among these participants [6]. Givan Bryan's background is to find out whether there is a relationship between e-commerce and the ease and trust of customers who buy goods online. Through this ease and trust, whether online purchases of goods are increasing, what factors lead to the increase in sales, and the variables that affect the increase in sales [7]. The participation of customers as data analysts enables companies to gain valuable insights and create value from big data. Awan Usama provided a theoretical explanation from a resource-based perspective on the impact of customer engagement as data analysts and the development of big data analysis capabilities in a business to business environment on manufacturing flexibility and performance [8].

The empirical results of Ullal Mithun S show that online reviews will affect consumer attitudes and significantly affect e-commerce sales in India [9]. Electronic commerce plays an important role in promoting information technology and communication. Taher Ghada elaborated on the main characteristics of e-commerce and its disadvantages to organizations and customers. It is important to understand the benefits and disadvantages, because the benefits of customers may be translated into the disadvantages of business organizations. Prosperous business organizations are very clear about their advantages and disadvantages before making any business decisions [10]. Maseeh Haroon Iqbal shows that risk perception will cause privacy concerns, while interest perception, familiarity, reputation, privacy policy and trust will alleviate privacy concerns, and thus affect customers' attitude and use of e-commerce platforms [11]. The purpose of Chiu Weisheng is to investigate the impact of brand leadership on satisfaction and repurchase intention on e-commerce websites. In addition, the different roles of gender and age have been explored in the proposed model [12]. The purpose of Suharto S is to analyze the impact of social media marketing on e-commerce customer satisfaction and loyalty. This study provides insight into the importance of consumer loyalty in the e-commerce industry. The method used in this study uses quantitative methods through investigation [13].

This paper studies the impact of online e-commerce interaction on consumer satisfaction based on big data algorithm, and studies the relationship between interactive data in online shopping and consumer satisfaction. Based on the perspective of interaction, this paper introduces the mediating variable of consumer satisfaction, constructs a model between interaction and trust, studies the internal influence mechanism of online interaction on customer satisfaction in online shopping, and proposes specific targets based on the conclusions drawn. At present, it is engaged in the management of e-commerce merchants in the evaluation category and points out the research limitations and future development directions.

2. E-commerce text mining under big data

2.1. Text characteristics of e-commerce data

"Information" plays an increasingly prominent role in e-commerce. How to analyze customers' needs and reflect their opinions through "information" is the biggest competitive advantage of e-commerce enterprises. Traditional enterprises such as banks and telecommunications are mostly structural data; Baidu, Tencent and other network companies mainly source their data from online reviews and user logs, rather than structural and semi structural ones. The data of e-commerce is between the two: users place orders, warehousing, sorting, distribution, and the data on the chain are structural; Data such as browsing behavior and purchase evaluation are unorganized. E-Commerce should combine the two to achieve customer insight, user positioning, risk assessment and other analysis and decision-making. To achieve accurate marketing, the key is to establish the user model, that is, the user image. The analysis of big data can also improve the user experience, and it can also realize the unified management of express delivery through big data.

Configuration e-commerce data description text features compared with ordinary text, IED configuration data description text usually involves e-commerce proper nouns [14]. Misdivision of words is easy to occur in the word segmentation stage, which leads to misclustering of word vectors by the language model [15]. Therefore, the article is in the classification package. Introducing custom proper nouns to improve the accuracy of word vector expression [16]. At the same time, the text often appears mixed in Chinese and English, the description is semi-structured, and there are some differences in text expressions, such as "link 3GOOSE receiving a network disconnected", "process layer a network GOCB1 GOOSE receiving interruption", using the expert system. It is difficult to control the expansion and completeness of inference rules when performing automatic mapping, resulting in redundancy or loss of rules in the rule base, leading to misclassification [17]. The article model comprehensively considers the above characteristics in the text representation stage, effectively ensuring the accuracy of the text representation vector.

The word2vec (including CBOW and Skip-Gram) text representation model constructed based on BP neural network can effectively reduce the dimensionality and sparsity of word vectors, and improve the mapping ability of the vector to the semantic relationship of the original text [18,19]. This model sets a local text analysis window. Assuming that the context word vector in the window is known, the maximization of the occurrence probability of the central word is used as the training objective to solve the model to realize the mapping of each word in the semantic space and obtain the dense static word vector after dimensionality reduction [20].

For filter layer design and preference matching, the role of the filter layer is to complete the matching calculation through the collaborative filtering algorithm, which is divided into two steps: generating a similarity list and performing matching according to the similarity [21]. This research is optimized on the basis of the traditional collaborative filtering algorithm. Traditional CF uses an inverted index to generate a co-occurrence matrix, and calculates the similarity between users (commodities) based on the co-occurrence matrix, and then filters the corresponding recommendation information [22]. The above algorithm has the problem of time and space loss caused by repeatedly scanning the intermediate table [23]. You can directly generate a "user-commodity" two-tuple to establish a set of mapping relations between the two to optimize the original algorithm [24]. When you need to use a user information table or an inverted index table, you can directly pass the aggregation operation with a time complexity of O (1) to realize [25]. That is, use the user ID as the key and the product ID as the value, and use the groupby function to form a user information table; then use the product ID as the key and the user ID as the value to use the groupby function to form an inverted index table [26]. Based on these two tables, a compressed co-occurrence matrix is generated [27]. The advantage of doing so is that it can save scan time during generation and large-scale compression (with a large number of zero elements) matrix to reduce space-time loss.

After calculating the similarity, select a set similarity threshold and filter out users who do not meet this threshold to complete the match. After integrating into the context of "theme", it is necessary to filter out the results that do not match the current theme when matching. After integrating into the context, the overall matching spatio-temporal complexity metric level remains unchanged, but the matching information of the scene is increased, which theoretically enhances the accuracy of the matching result. The sorting layer is mainly used to determine the priority of different commodities to different users in different situations. When sorting, there may be problems of heterogeneity of data and explosion of dimensionality, and the data needs to be encoded and dimensionally reduced. Because there are two types of qualitative and quantitative data in the objective situation, the former cannot be directly mapped with the numerical value, and one-hot encoding processing (One-hot Encoding) is required in advance. Some qualitative fields may have many different values. After the one-hot encoding vector is expanded, problems such as dimensional explosion will occur during model training, and the response time will also be reduced. In this case, principal component analysis (PCA) can be used for dimensionality reduction. After completing these two steps, a series of CTR prediction models can be trained to predict the likelihood of users clicking. Sort in descending order according to the predicted CTR value, and select the Top N product recommendation with the largest CTR value.

Rule layer design and cold start optimization. The output result of the sorting layer is usually not directly displayed to the user, but is displayed after some sorting rules are optimized. There are two main problems that this step solves: Cold-start and Re-ranking. The cold start problem is essentially a "multi-armed slot machine problem", which can be solved using the Bandit algorithm integrated into the context. The reason for setting the reordering function module is that some special business requirements need to reorder the sorted results. In the rule layer, you can set up specific sorting rules for specific businesses and add new sorting constraints to complete the re-sorting. For example, for the food channel of an e-commerce platform, sometimes the top 5 products recommended in the business rules contain both snacks and drinks to achieve matching promotion. If the actual recommended Top 5 results only contain snacks, you need to follow this one.

2.2. Online interactive text mining model

Online e-commerce interaction refers to real-time interaction on websites, social media, or other digital channels, including online chat, customer support, social media comments and feedback, and so on. This form of interaction has become an important component of e-commerce, which has a positive impact on improving user experience, increasing sales, and promoting brand loyalty. One of the main advantages of online e-commerce interaction is its ability to improve user satisfaction. By responding to user issues and needs in real-time, companies can better establish contact with customers, solve problems and provide support in a timely manner, and improve customer satisfaction. In addition, online e-commerce interaction can help customers better understand products or services, enhance their purchasing intention, and thereby increase sales and conversion rates.

(1) The extraction of consumer dialogue evaluation elements

Consumer text dialogue has the characteristics of less labeled data and more errors. However, traditional methods only use dependency syntax tools to extract word relationships, resulting in a relatively large database of extracted corpus. Therefore, the model is based on a two-way communication framework, firstly acquiring sentiment words and evaluation attributes from external corpus and expanding them. Then, the word vector-based corpus similarity calculation method is used to identify long-tail words, and finally the emotional words and evaluation attributes of the consumer dialogue text are mined. Use external corpus data set and two-way propagation algorithm to obtain initial sentiment words and evaluation attributes (As shown in formulas 1 to 3):

$$I = f(W^e D_1 + \delta^e) \tag{1}$$

$$D_a = g\left(W^d I + \delta^d\right) \tag{2}$$

$$j = \sum_{k=1}^{k} \sum_{i \in Ck} |x_i - u_k|^2 \tag{3}$$

Among them, x is each data object in the sample, u is the center of the class, C is the class. The degree of distortion of each class is equal to the sum of the squares of the distance between the center of the class and the position of its internal members, and the cost function is the sum of the degree of distortion of each class. Manually filter the initial sentiment words and evaluation attributes obtained in the previous step to eliminate wrong words (As shown in formulas 4 to 6):

$$f(x) = \sum_{j \subset Q} c_j \frac{x_j}{\sigma\left(X_j'\right)} - p \tag{4}$$

$$P\left(d_i, w_j\right) = P(d_i) P\left(w_j | d_i\right); P\left(w_j | d_i\right) = \sum_{k=1}^{K} P\left(w_j | z_k\right) P(z_k | d_i) \tag{5}$$

$$DBI = \frac{1}{k} \sum_{i=1}^{k} \max_{j:i} \left\{ \frac{\mathrm{Dintra}(Ci) + \mathrm{Dintra}(Cj)}{\mathrm{Dinter}(Ci, Cj)} \right\} \tag{6}$$

Among them, $\mathrm{Dintra}(Ci)$ represents a cluster Ci all other users in Ci the average distance of the centroid of $\mathrm{Dinter}(Ci, Cj)$ represents the distance between the cluster and the center of mass. Use the two-way propagation algorithm to refine the filtered emotional words and evaluation attributes, and obtain the emotional words and evaluation attributes suitable for consumer dialogue text mining (As shown in formulas 7 to 9):

$$Sd_{gain}(Y) = \frac{\sigma(Y) - avg(\sigma(Y'), \sigma(Y'))}{\sigma(Y)} \tag{7}$$

$$\mathrm{C(k)} = [\zeta_1 \mathrm{c}_1(\mathrm{t}) + \zeta_2 \mathrm{c}_2(\mathrm{k}) + \zeta_3 \mathrm{c}_3(\mathrm{k}) + \zeta_4 \mathrm{c}_4(\mathrm{k}) + \zeta_5 \mathrm{c}_5(\mathrm{k}) + \zeta_6 \mathrm{w}_{\mathrm{ik}}] \tag{8}$$

$$c_1(t) \geq 0, c_2(k) \geq 0, c_3(k) \geq 0, c_4(k) \geq 0, c_5(k) \geq 0 \tag{9}$$

(2) Extraction of evaluation elements from external corpus

The evaluation elements are extracted by collecting consumer-related comments and Weibo comments as external corpus, and then 11 kinds of syntactic rules are designed to extract relational word pairs according to the proposed dependency relationships. Among them, the emotional word (S) is limited to adjectives, and the evaluation attribute (A) is limited to verbs or nouns. Based on these rules, the flow of the two-way propagation algorithm for the external corpus can be obtained. First, candidate relationship pairs are extracted, and 11 syntactic rules are used to extract the candidate relationships of all sentences in the external corpus data set (As shown in formulas 10 to 11):

$$\min w_k(t) = \left[\omega_1\left(\frac{d_k}{V}\right) + \omega_2\left(\frac{d_k}{V}\right) + \omega_3\left(\frac{T_k}{ND_K}\right) + \omega_1(P_K T_K)\right] \tag{10}$$

$$\vartheta = \frac{2k}{k+1} + \frac{2c_1 + c_2 + 3et - 2et\zeta}{3} \tag{11}$$

Iteratively identify evaluation elements, use the improved two-way propagation algorithm proposed in this paper to iteratively identify candidate emotional words and attribute words, and filter them by word frequency (As shown in formulas 12 to 14):

$$(\mathrm{In} - \alpha \mathrm{W})\mathrm{y} = (\mathrm{In} - \alpha \mathrm{W})\mathrm{X}\beta + \varepsilon \tag{12}$$

$$\wp_\kappa = \frac{2k}{k+1} + \left[\frac{1}{2} + \frac{1}{2k}\right]\left[\frac{c_2 - c_1}{3}\right]^2 + \frac{2(c_2 - c_1)}{3} \tag{13}$$

$$\psi = \sum_{x=1}^{\theta} Vx = \sum_{x=1}^{\vartheta}\left(\frac{Wx}{\sum_{1}^{n} W_{\mathfrak{Z}}} Sx\right) \tag{14}$$

Among them (As shown in formulas 15 to 16):

$$\Delta Q_L + \Delta Q_S + \Delta Q_R = \Delta Q \tag{15}$$

$$w_{ik} = \sum_{a}^{n} \tau_1 X_{ik} + \sum_{b}^{n} \tau_2 U(Y_{ik}) + B_{ik} \tag{16}$$

The algorithm extracts all kinds of relationship rules at one time and stores them in the collection of <attribute words, attribute words>, <attribute words, sentiment words> and <emotional words, sentiment words>. At the same time, each set uses HashSet to speed up the matching speed.

(3) Extraction of evaluation elements of consumer corpus

Due to the high degree of colloquialization and many textual errors in consumer corpus, it is impossible to analyze the syntactic dependencies well. This paper explores structured customer opinion information, and uses relationship rules based on window and part of speech to capture the relationship between emotional words and attribute words. In this paper, emotion words are set as existing emotion words or part-of-speech adjectives a, and attribute words are restricted to verb v or noun n, and then part of speech restriction and sliding window rules are used to extract relational pairs. The relationship rule designed for the characteristics of the consumer corpus in the article is: if there are nouns or verbs in the sliding window S, and there are existing emotional words or adjectives, and the relationship rules shown in Table 1 below are satisfied, the nouns or verbs. There are emotional words or adjectives as relational pairs. The dependency relationship rules defined above extract candidate relationship pairs, and use the support threshold to filter them, and obtain the relationship pairs with the support threshold greater than K1(As shown in formulas 17):

$$MES(y, y') = \frac{\sum_{i=1}^{m}(y_i - y_i')}{m} \tag{17}$$

Use the relationship rules in Table 1 to extract the relationship pairs in the consumer dialogue text, and filter them to obtain the relationship pairs with a support threshold greater than K2(As shown in formulas 18):

$$L_r = \|D_I - D_O\|_2 \tag{18}$$

Combine the relationship pairs in step 1 and step 2, and take the maximum value of each relationship pair to obtain candidate relationship pairs (As shown in formulas 19 to 20):

$$f_R{}^{A_i} = w_G{}^{A_i A_j} \cdot V \tag{19}$$

Table 1
Reliability and validity analysis results.

Latent variable	Measuring	Item	Factor	Load	Cronbach	KMO	Latent
Customers	1.87	1.73	1.55	1.04	1.91	1.44	1.13
Site interaction	3.46	2.63	1.08	2.22	1.59	3.89	1.57
Estimate	3.07	4.64	5.71	4.05	4.05	3.06	5.56
Seller	5.86	4.52	3.33	5.13	1.16	4.01	2.06
Interaction	4.96	1.65	1.48	2.63	3.5	2.42	4.32
variable	3.28	3.11	3.15	3.08	1.43	4.86	1.97

$$w_G{}^{A_iA_j} = \max\left\{0, W_G \cdot \varepsilon\left(f_G{}^{A_i}, f_G{}^{A_j}\right)\right\} \tag{20}$$

Then use the two-way propagation algorithm introduced in Part 1 to identify the above candidate relationship pairs in two-way propagation and filter them by word frequency.

(4) Low-frequency word extraction

This model uses the Word2Vec model to map words to a multi-dimensional real vector space to solve the problem that similar words may have exactly the same representation in the discrete language model. The model includes a Skip-gram probability model that predicts context words based on current words and a CBOW model that predicts current words based on context words. This paper calculates the cosine distance between two words in a multi-dimensional real vector space to obtain the similarity between different words, as shown in the following formula (As shown in formulas 21 to 24):

$$overlap = \frac{R^g \cap R^r}{R^g \cup R^r} \tag{21}$$

$$P\left(d_i, w_j\right) = P(d_i)P\left(w_j|d_i\right); P\left(w_j|d_i\right) = \sum_{k=1}^{K} P\left(w_j|z_k\right)P(z_k|d_i) \tag{22}$$

$$\lambda(Ai, Aj) = \left[\log\left(\frac{\left|x_{A_i} - a_{A_j}\right|}{w_{A_j}}\right), \log\left(\frac{\left|y_{A_i} - y_{A_j}\right|}{h_{A_j}}\right), \log\left(\frac{w_{A_i}}{w_{A_j}}\right), \log\left(\frac{h_{A_i}}{h_{A_j}}\right)\right] \tag{23}$$

$$VectorSim = (\Phi_a, \Phi_b) = \frac{\Phi_a^T \Phi_b}{\|\Phi_a\|\|\Phi_b\|} \tag{24}$$

In the formula, a and b are the vector representations of the words a and b, respectively. However, because some corpus in the consumer dialogue text is frequently mentioned, there is a long tail phenomenon. Therefore, this paper digs out more emotional words and attribute words from the long-tail words to improve accuracy. The specific method is as follows:

1) Select the low-frequency word lowS of the emotion set and the low-frequency word lowA of the attribute word set, the accurate low-frequency word set S and the accurate attribute word set A, and set the similarity threshold;
2) For each word in lowA, if sim (word, A), add word to the recommended attribute word set addA;
3) For each word Word in lowS, if sim (word, S), then add Word to the recommended emotional word set addS;
4) Output the recommended emotion

The word set addS and the recommended attribute word set add A. Among them, the similarity of two words sim (word, W) is the maximum similarity of Word relative to all words in the set W, namely (As shown in formulas 25 to 26):

$$Zi = R_i^1 + B_i^1, i = 1, 2, ..., n \tag{25}$$

$$sim(word, W) = \max_{w_i \in w}(VectorSim(word, w_i)) \tag{26}$$

(5) Phrase expansion

Because words cannot fully express the meaning of a sentence in many cases, the two-way propagation algorithm used in this article needs to iteratively identify emotional words and attribute words. At the same time, the rule-based method cannot handle the problem of attribute phrase extraction well. Therefore, this paper designs a phrase expansion method based on left and right information entropy and mutual information between points. Information entropy is a measure of uncertainty. Assuming that the number of values of random variable X is limited, the probability of its value being x is P(x), so the entropy of variable X is (As shown in formulas 27 to 29):

$$H(X) = -\sum_{x \in X} P(x)\log_2 P(x) \tag{27}$$

The left and right entropy of the word W is defined as:

$$H_L(X) = -\sum_{\forall Wa \in A} P(Wa|W)\log 2(Wa|W) \tag{28}$$

$$H_R(X) = -\sum_{\forall Wb \in A} P(Wb|W)\log 2(Wb|W) \tag{29}$$

Among them, *Wa* and *Wb* are the set of words on the left and the set of words on the right of word W, respectively. The mutual information between points is a measure of the degree of mutual dependence of two variables, which is defined as (As shown in formulas 30):

$$PMI(w1, w2) = log\,2\frac{P(w1\&w2)}{P(w1)P(w2)} \tag{30}$$

In the formula, P (w1), P (w2), P (w1&w2) are the frequency of occurrence of word w1, the frequency of word w2 and the frequency of word w1 and word w2. The higher the mutual information between the points, the higher the correlation between the two words, that is, when the two words have higher mutual information between the points, the higher the correlation between the two words; on the contrary, when the two words have lower mutual information between the points. When it comes to information, the correlation between the two words is also low. Using information entropy and mutual information between points, the attribute words extracted by the two-way propagation algorithm can be combined into some attribute phrases. For example, the words “real-time” and “mode” can be combined into the phrase “real-time mode".

3. Construction of e-commerce interactive data model based on big data algorithm

3.1. E-commerce interaction data sources

According to online shopping data, it can be known that clothing occupies the largest market share in the online shopping market, and women’s clothing products account for most of the market share. In addition, women’s clothing target consumers have a higher level of participation, more diversified shopping goals and a higher level of shopping frequency when shopping. In addition, the shopping needs and shopping preferences of these consumers are also very significant. Jingdong interactive shopping platform is the research field, and the target consumer satisfaction of the women’s clothing interactive shopping platform is used as the research object for analysis and exploration.

3.2. Content and steps

In the experimental analysis of this article, the recorded evaluations were used as stimulus materials, and different groups of participants were selected in the three experiments. In the experiment of testing the results and filling in the questionnaire, the recorded evaluations are used as stimulus materials into practice, and finally the test results are counted, and the experiment participants are asked to fill in the relevant questionnaires. In the design of the questionnaire in this article, one of the elements of the survey link is to allow users to choose from most online shopping stores specified in the questionnaire based on the type of stores they have recently viewed. If there is no target shopping store, users can not only fill in the options provided by the questionnaire, but also fill in the name of the online store they recently browsed.

The questionnaire is used to judge the validity of the items not selected by the online shopping store after the collection. Except for the number of social media software that cannot be accurately counted in this questionnaire survey, the total number of statistics that can be performed is more than 1,400, of which the number of questionnaires received is 823. After screening according to the principle of effective judgment, the number of valid questionnaires. With 674 copies, it can be concluded that the effective response rate of the questionnaire was 82%. In the validity questionnaire, in terms of gender, the ratio of men to women is not much different; in terms of age, the proportion of young people is 32%, the proportion of middle-aged people is 61%, and the proportion of elderly people is 7%, the proportion of ordinary education is 65%, and the proportion of advanced education is 31%; from the perspective of income, the low monthly salary accounts for the majority of the proportion.

3.3. Hypothesis

(1) Online interaction and satisfaction

There are few related academic researches on the relationship between interaction and satisfaction theory in online shopping behavior, but some research materials support the promotion of the two. Based on the research results of scholars, this article proposes the following hypotheses:

H1. Customer satisfaction is positively correlated with the interaction in the online shopping process. The interaction modes in the online shopping process are divided into three categories as follows: interaction between customers and websites, interaction between customers and merchants, and interaction between customers and customers. Combine the above three classification results into the satisfaction theory. The two types of satisfaction classification proposed the following hypotheses:

H1a. Customer satisfaction is positively related to the degree of interaction between customers and the website.

H1b. Customer satisfaction is positively related to the interaction between customers and businesses.

H1c. Customer satisfaction has a positive effect on the interaction mechanism between customers.

(2) Online interaction and perceived risk

For the research on interaction and risk perception in the field of online shopping, most scholars adopt indirect research methods, and few scholars associate the two. But from the relevant research content, there is a close connection between the two. In summary, the following hypotheses are put forward: H2: There is an obvious negative correlation between the formation of customer perceived risk and the interaction in the online shopping process.

H2a. There is an obvious negative correlation between the formation of customer perceived risk and the interaction between customers and the website.

H2b. There is an obvious negative correlation between the formation of customer perceived risk and the interaction between customers and businesses.

4. Influence of E-commerce interaction on consumer satisfaction

4.1. Influence of capable services on consumer satisfaction

To ensure the effectiveness of this survey, the statistical data of the survey was tested for credibility and validity. The indicators of the reliability test are the Cron-bach coefficient and the latent variables derived from the measurement items. The results of the reliability and validity analysis are shown in Table 1.

As shown in Fig. 1, the Cronbach coefficient values of this survey are all higher than 0.4, and the credibility value is 0.91. Therefore, it is concluded that the results of this test have good credibility. In the validity test, first select the indicators KMO and Bartlett to perform factor analysis matching experiments on the sample data, and calculate the factor loads on the latent variables after ensuring that they are suitable for validity analysis. The final test results show that the factor loads are greater than 0.7, indicating that the results of this survey questionnaire have good validity.

As shown in Table 2, H2a is significant, but H2b and H3a are just the opposite. This result indicates that there is no effective feedback mechanism between the establishment of incompetent satisfaction and the establishment of customer satisfaction. The establishment of customer space satisfaction has formed an effective feedback effect mechanism; the establishment of customer satisfaction with online store capabilities is mainly derived from some objective factors that the online store gives customers, such as the size of the online store and the funds of the online store strength, etc., if the online store can provide customers with high-quality resources and services while allowing customers to feel that such transactions are extremely secure, then when the customer's spatial satisfaction is established, this spatial satisfaction can make customers produce a feeling as if I have verified that the online store has excellent capabilities. In this way, when spatial satisfaction is generated in the minds of customers, ability satisfaction can be positively affected by its feedback effect mechanism.

As shown in Fig. 2, the structural validity of each variable was measured by KMO and Bartlett sphere test. After testing, the KMO value of the overall variable of the questionnaire was 0.938 (>0.6), the approximate chi-square was 9758.347, and the significance was 0.000. The variable reliability and validity analysis is shown in Table 3. The results show that the commonality of the item items in all variable dimensions is greater than 0.6, indicating that the factors in the study items have a good correlation, and the factor loads are all greater than 0.7 (the absolute value of the factor loading coefficient is greater than 0.4), which means that the data in the questionnaire has high convergence and good structure validity.

The path coefficients of the structural equation model are shown in Fig. 3. The structural equation model analysis uses the AMOS23.0 software to draw a model of the factors that affect consumers' satisfaction with Internet e-commerce shopping, and make a preliminary estimate of the model's fit, based on the results.

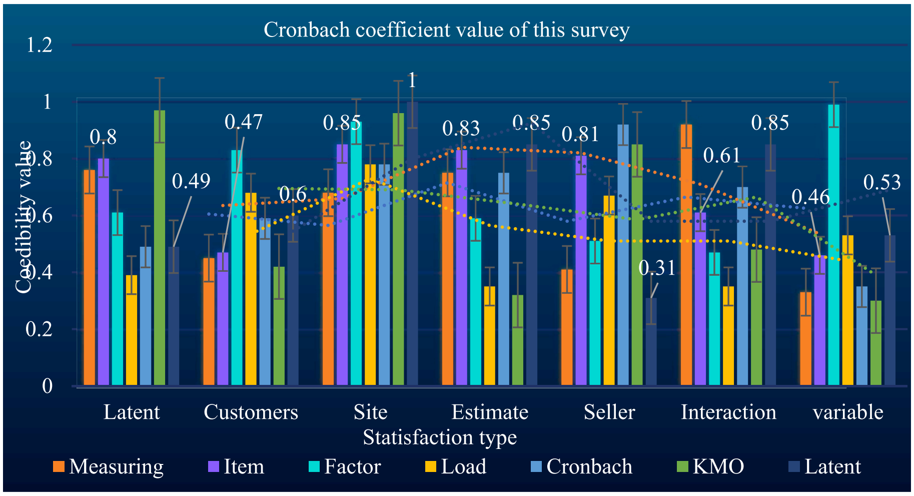

Fig. 1. Cronbach coefficient value of this survey.

Table 2
Efforts and performance expectations and the impact of the optimal combination.

Hypothesis	standardization	Path coefficient	S.E.	C.R.	P	Label
H1a	1.66	0.57	0.29	0.06	1.4	1.09
H1b	3.23	1.57	3.5	2.32	1.67	3.93
H2a	5.12	4.78	4.78	2.16	3.41	2.78
H2b	4.39	4.18	3.62	4.43	5.87	2.84
H3a	3.18	1.57	4.84	2.61	4.76	2.13
H3b	5.47	1.06	6.98	2.6	5.85	5.57

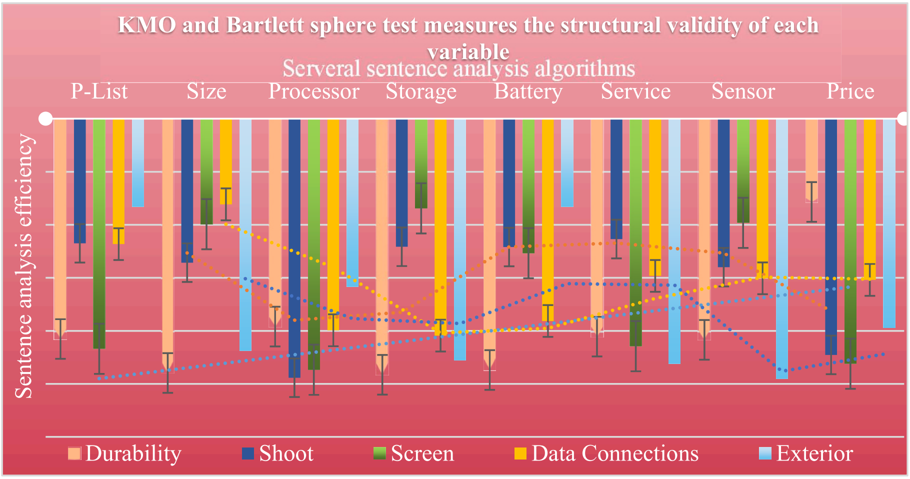

Fig. 2. KMO and Bartlett sphere test measures the structural validity of each variable.

Table 3
The profit of each node of the supply chain and the relationship between total satisfaction.

Project	innovation	Satisfaction	Use behavior	TextLength	Readability	Subjectivity
Options	1.42	1.09	1.84	0.42	1.94	0.88
Frequency	1.67	3.93	1.42	1.55	3.29	2.99
Proportion	3.41	2.78	2.08	5.33	2.71	2.55
service	5.87	2.84	2.22	1.43	4.99	4.56
Individual	4.76	2.13	4.67	3.51	3.42	4.69

As shown in Fig. 4, except that the H3a hypothesis is not valid, the CR values of the other hypotheses are all greater than 1.96, which passed the significance level verification. The SE values in the table are all less than 1, indicating that the error is small. In addition, the standardized coefficients of H1a and H1b paths are 0.131 and 0.118, respectively, which are slightly smaller, indicating that social influence and perceived risk have little effect on consumer satisfaction. At the same time, CR in H1 is a positive number, and the direction of influence is positive, which is contrary to the assumption. Therefore, the initial model needs to be corrected. After the correction, GFI value is 0.816, AGFI value is 0.825, RMSEA value is 0.042, TFI value is 0.930, CFI value is 0.955, PGFI value is 0.718, PNFI value is 0.810, fitting. The degrees are all within the acceptable range.

As shown in Fig. 5, according to the method of simulation analysis, four models are used for variable selection and parameter estimation. The PIPL model selects 20 variables, which is less than the three comparison methods. Among them, 10 variables appear in the prior information set, and their prior frequencies are basically above 50. This shows that the PIPL model can properly absorb prior information and is not completely controlled by the prior information.

4.2. Impact of service provision on consumer satisfaction

As shown in Fig. 6, this part mainly analyzes its dissatisfaction, the share of technology input costs, the price elasticity coefficient, and the logistics service level elasticity coefficient on the profit and profit of e-commerce platforms and third-party logistics service providers before and after the blockchain application. The impact of the total profit, the stronger (weak) the seller and the customer's interactive activities, the higher (lower) the level of customer trust establishment.

As shown in Table 3, when the blockchain technology is not adopted, the profits and total profits of each node enterprise in the supply chain decrease with the continuous increase of dissatisfaction, which shows that the third-party logistics service providers only

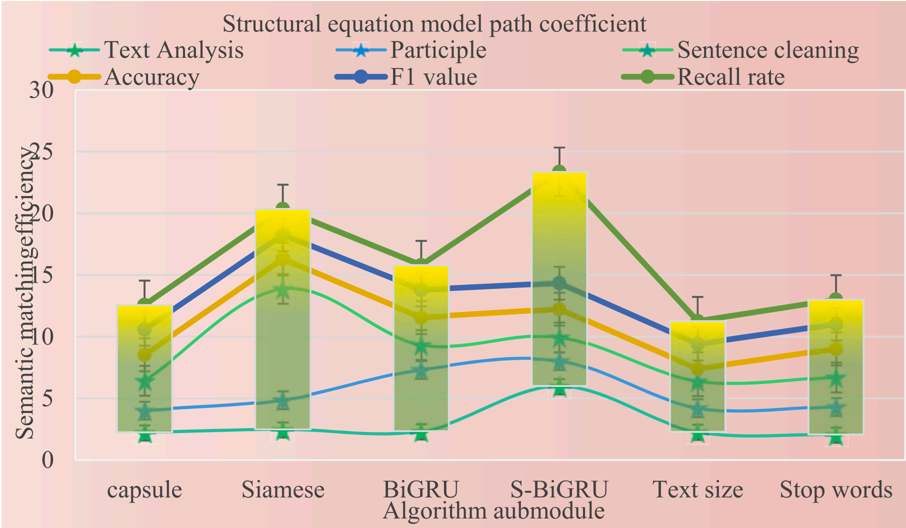

Fig. 3. Structural equation model path coefficient.

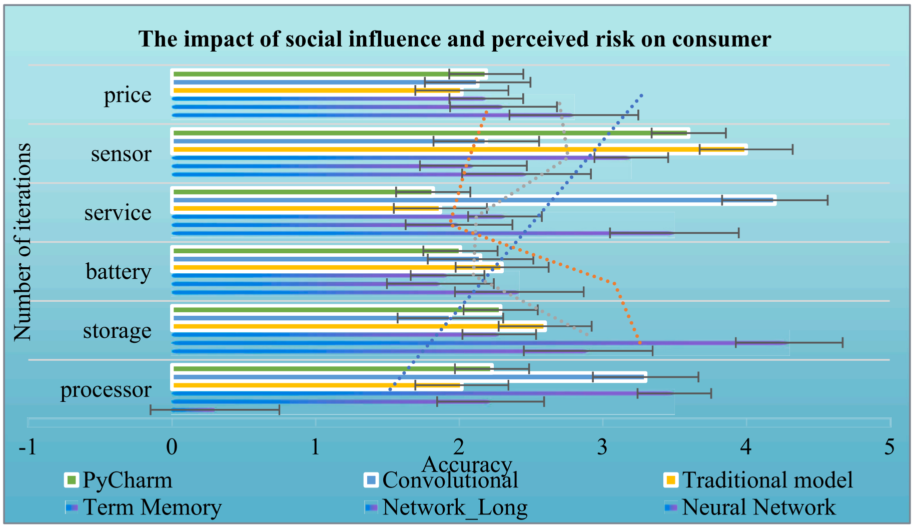

Fig. 4. The impact of social influence and perceived risk on consumer.

consider their own profits and damage. The long-term development of the entire supply chain, as the third-party logistics service provider reduces the level of logistics services, which results in the shift or reduction of market demand, I thought it was profitable for myself, but I did not know that it would affect the long-term operation of the company and damage the supply chain partners, and the coordinated development of the supply chain. It is the effective and feasible way for enterprises at each node of the supply chain to maximize their own interests.

As shown in Fig. 7, the profit of the e-commerce platform, the profit of the third-party logistics service provider, and the total profit of the supply chain are all declining with the increase of the price elasticity coefficient. This shows that when the blockchain technology is adopted. The higher the selling price, the more advantageous it is. Only by adopting a reasonable selling price in line with customers can it bring more benefits to the enterprise. The profits of third-party logistics service providers increase with the increase in the elasticity coefficient of logistics services. The profits of the e-commerce platform and the total profit of the supply chain first decrease and then increase with the increase in the elasticity coefficient of the logistics service level, which indicates the adoption of blockchain. When it comes to technology, third-party logistics service providers take to provide high-quality logistics services is an effective measure for their own benefit. The profit fluctuation of e-commerce platforms is deeply affected by their service levels.

As shown in Table 4, the effect of effort expectations, performance expectations, and optimal combination shows that consumers believe that Internet shopping services are easy to use and can bring additional information and assistance to consumers, simplifying consumers through the best configuration of the shopping system. Using processes and improving operational efficiency will increase

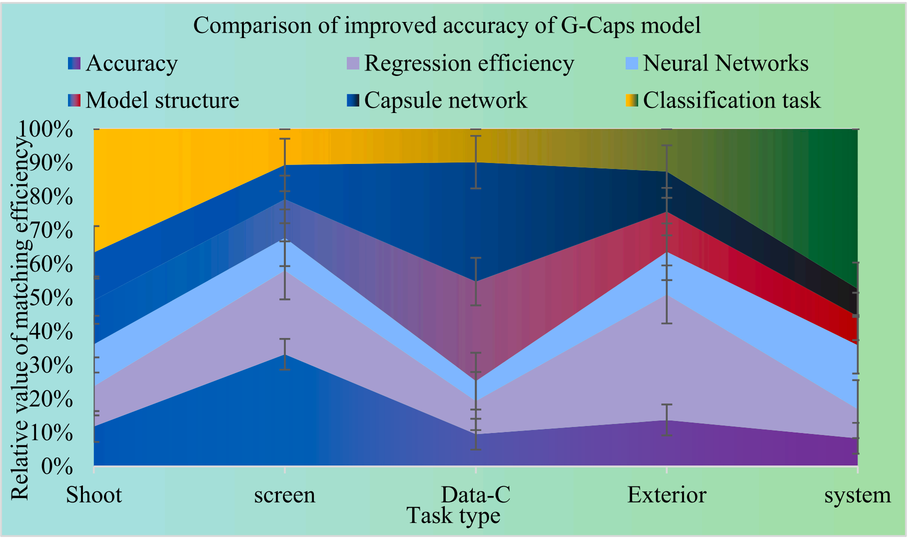

Fig. 5. PIPL model can properly absorb prior information.

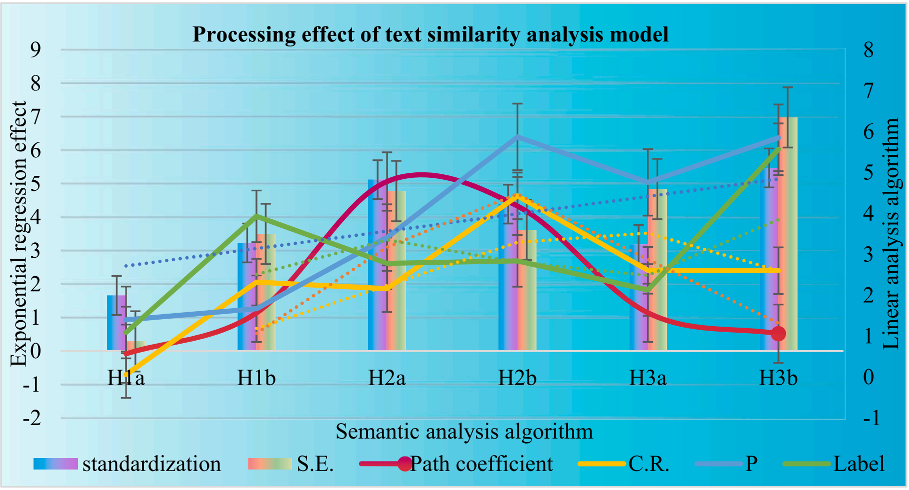

Fig. 6. The impact of elasticity on e-commerce platforms before and after blockchain application.

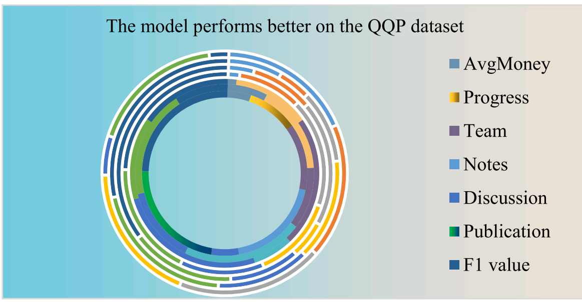

Fig. 7. Reasonable sales price can bring more benefits to the enterprise.

consumer satisfaction. The reason why individual innovation has a large effect on other variables is that the current Internet shopping popularity is not comprehensive. Only users with strong individual innovation can actively pay attention to new technologies and products, get in touch with new things, and have a greater impact on the ease of use and products. Convenience has higher expectations

Table 4
Actual operating data of an e-commerce platform.

Item	Proportion	Frequency	service	Individual	Satisfaction	behavior
AvgMoney	1.31	1.5	0.28	0.51	0.81	1.92
Progress	2.84	3.33	2.54	2.82	1.98	1.17
Team	3.7	2.31	4.25	4.77	3.94	2.61
Notes	5.37	4.55	1.32	3.68	1.17	3.61
Discussion	1.53	2.86	4.88	3.68	2.2	3.32
Publication	6.46	4.04	2.69	5.02	3.27	5.2

and a more accurate prediction of possible risks. From the influence of facilitating factors and service pricing, it can be concluded that the algorithm optimization of the system back-end needs to be considered in the design to improve the effectiveness and timeliness of system feedback, consider the reasonableness and transparency of prices, and improve consumer satisfaction.

As shown in Fig. 8, when customers are at a low or high degree of satisfaction tendency, if the way to create satisfaction with their online shopping is achieved through satisfaction stimulated by the interaction of the website, the impact will not be effective. It will be obvious. This is because customers are very sensible when they are in a low-satisfaction tendency. They use rational thinking to think about online shopping behavior, and the above influence models are based on perceptual thinking as the experience basis, so they will not work; when customers. At a high degree of satisfaction tendency, the effect should be more obvious according to common sense, but the results here are not obvious. This may be caused by data or scale problems, or it may be due to high satisfaction tendency customers. They are all subjectively willing to establish a satisfaction mechanism for them, without the influence of external factors.

As shown in Table 5, effort expectations, performance expectations, and optimized combinations have a significant positive impact on satisfaction. From the standardized coefficient hypothesis, the standardized path coefficient shows that performance expectations (0.326) have a greater impact on satisfaction than the optimized combinations (0.304) and effort expectation (0.269). At the same time, effort expectation has a significant impact on performance expectation. Individual innovation positively affects effort expectation, perceived risk, optimized portfolio, and service pricing. The order of impact is optimized portfolio (0.584), effort expectation (0.419), perceived risk (0.404), service pricing (0.393), satisfaction, facilitating factors and service pricing have a significant positive impact on usage behavior, while social impact and service pricing have little effect on satisfaction.

As shown in Fig. 9, in the H2 series of hypotheses, both H2a and H2c have significant effects, but H2b does not have such a significant effect, indicating that the way to reduce the perceived risk of customers can be through the establishment of interaction between customers and the website and customers. The establishment of interaction between the two parties can be achieved, but the interaction between customers and businesses does not have the effect of reducing perceived risks. Therefore, in terms of reducing perceived risk, the interaction between customers and merchants has no obvious effect on it.

5. Discussion

With the continuous development of Internet technology, more and more consumers are shopping through e-commerce platforms. However, due to the diversity and personalization of consumer needs, e-commerce platforms need to continuously improve and optimize their interactive experience to improve user satisfaction and loyalty. In this regard, text mining techniques and empirical analysis methods can play an important role. Specifically, we can consider the following aspects:

Use text mining technology to analyze user feedback: Through text mining of user feedback data, you can deeply understand user needs and pain points, thereby targeted improvement of e-commerce platform products and services. For example, emotional analysis

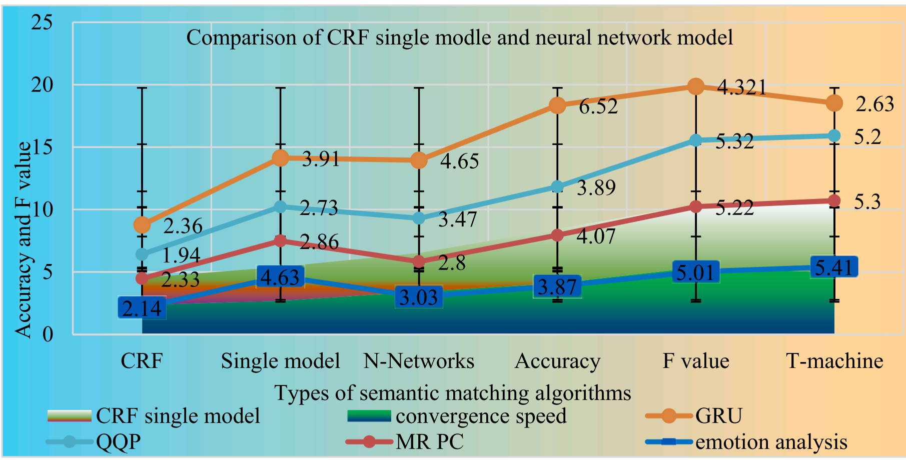

Fig. 8. Satisfaction inspired by website interactivity.

Table 5
Social impact and service pricing impact on satisfaction.

Product Properties	Durability	Shoot	Screen	Data Connections	Exterior
Packing List	0.831	0.47	0.868	0.473	0.332
Size	0.959	0.543	0.398	0.323	0.875
Processor	0.784	0.977	0.947	0.798	0.633
Storage	0.966	0.483	0.338	0.818	0.912
Battery	0.948	0.484	0.507	0.763	0.332
Service	0.822	0.454	0.858	0.593	0.924
Sensor	0.834	0.56	0.393	0.602	0.981
Price	0.314	0.891	0.924	0.608	0.788

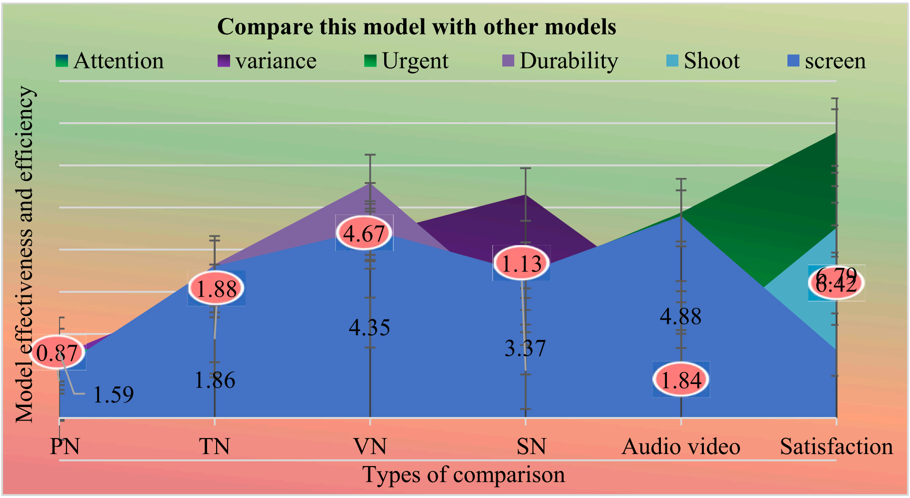

Fig. 9. Ways to reduce customer perceived risk.

techniques can be used to analyze emotional tendencies and satisfaction in user reviews, as well as specific evaluations and suggestions of users on products or services. This information can provide valuable references for e-commerce platforms to help them optimize their user experience and satisfaction.

Using empirical analysis methods to evaluate interaction effects: Through empirical analysis methods, it is possible to quantitatively evaluate the interaction effects of e-commerce platforms and identify key factors that affect user satisfaction. For example, you can compare the effects of different interaction methods and strategies through methods such as A/B testing, and make corresponding adjustments and improvements to the interactive experience of the platform based on the experimental results.

Reference to successful cases in other industries: In addition to the e-commerce industry, there are also many successful interactive experience cases in other industries that can be learned and applied to the e-commerce field. For example, you can learn from rich interaction design experience in the game industry and introduce game elements and interaction mechanisms into e-commerce platforms to improve user engagement and satisfaction.

In summary, using text mining technology and empirical analysis methods to optimize the interactive experience of e-commerce platforms can effectively improve user satisfaction and loyalty, thereby promoting the sustainable development of the e-commerce industry.

6. Conclusions

Compared with the general definition of e-commerce interaction, it is more necessary to scientifically analyze and define consumer satisfaction in combination with specific fields, specific research questions or research contexts. In particular, it is necessary to clarify whether the object of consumer satisfaction is a goal, event or behavior in different research fields. The field of social psychology has a wide range of research objects on consumer satisfaction, and the research objects in other fields need to be further expanded. In marketing, scholars pay more attention to the individual's consumer satisfaction with products and lack attention to objects such as product brands, crisis events or corporate behaviors. In addition, existing research on consumer satisfaction focuses on the simultaneous or short-term positive and negative attitudes. In fact, consumer satisfaction may change dynamically.

According to the theoretical framework of consumer satisfaction proposed in this article, consumption. The conflict effect of consumer satisfaction needs further exploration and confirmation. The influence of consumer satisfaction on the consistency of individual decision-making and attitude behavior may be interfered by some factors, such as personal knowledge level, preference certainty, cognitive needs and other internal psychological characteristics. The difference between Chinese and Western cultural values may have an impact on the moderating effect of consumer satisfaction, and the cultural values of dialectical thinking will promote the formation of consumer satisfaction, leading to a positive impact on consumer satisfaction. The influence of these internal psychological characteristics and external environmental factors on the relationship between consumer satisfaction and consumer decision-making process also needs to be verified in future research.

The results of the study found that the direct impact of consumer satisfaction on self-evaluation is not significant, and consumer satisfaction's perception of results and self-evaluation are affected by the valence of results. However, the research focuses on the difference between the consumer satisfaction of the stimulus target and the consumer satisfaction of the selected target in the decision-making context. Whether the research conclusion is robust in the decision-making context and whether the consumer satisfaction. Linking with other attitude indicators has an impact on the outcome of decision-making, which needs further exploration.

Although the study of online e-commerce interaction based on big data algorithms on consumer satisfaction is of great significance, there are still limitations. Big data algorithms require consumers to provide a large amount of personal and interactive data, which may involve consumer privacy and security issues. Secondly, big data algorithms may have data biases and errors, leading to inaccurate analysis results or misjudgments. In addition, big data algorithms may also have algorithmic black box issues, where the decision-making process of the algorithm is opaque and difficult to explain and understand.

In the future, online e-commerce interactions based on big data algorithms will continue to develop and improve. Firstly, as consumers focus on privacy and security issues, big data algorithms will place greater emphasis on data security and protecting personal privacy. Secondly, big data algorithms will place greater emphasis on data accuracy and interpretability. By improving the transparency and interpretability of algorithms, consumers will trust and accept the results of algorithms more.

To address the above issues, some corrective measures need to be taken. Firstly, strengthen data protection and privacy protection, and use technologies such as encryption and deidentification to ensure data security. Secondly, strengthen the control and management of data quality to improve the accuracy and reliability of data. Finally, strengthen the interpretability and transparency of the algorithm, so that users can better understand and trust the decision-making process and results of the algorithm.

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Author contribution statement

Li Li: Wrote the paper, Conceived and designed the experiments.
Lin YUAN: Performed the experiments; Analyzed and interpreted the data.
Juanjuan Tian: Contributed reagents, materials, analysis tools or data; Analyzed and interpreted the data.

Declaration of competing interest

The author states that this article has no conflict of interest.

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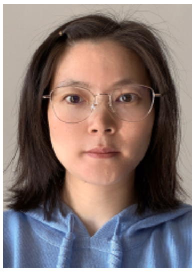

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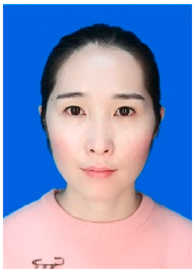

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