Research Article

Influence of Cultural Differences on the Establishment of Consumer Trust in a Socialized Cross-Border E-Commerce

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This research paper examines the necessity of identifying cultural issues in online globalization and emphasizes that payment and logistic systems, as well as language, are the most important variables that any company should consider during their online globalization process. With the rapid development of the network and the continuous integration of the world economy, cross-border e-commerce has become more important and convenient. However, there are a number of electronic transaction problems that hinder the smooth functioning of this concept, thus creating distrust between the parties to the transaction, such as non-delivery, inaccurate quantities of goods, fraudulent transactions and low-quality goods, which are related to cultural differences, quality problems of the goods themselves and many other aspects. There is huge room for cross-border e-commerce development, and there are trust problems such as fraud and false transactions in all development processes. Based on the factors of cultural differences and consumer trust, this paper establishes an evaluation model of consumer trust in cross-border e-commerce, including honesty, goodwill, and ability. This article uses deep learning to establish a credit evaluation model, analyzes credit evaluation indicators, and obtains the factors that affect cross-border trade under different cultures through experimental testing and analysis.

1. Introduction

As the Internet has spread and digital technology has evolved, e-commerce has exploded all over the world. The buyers first order the item and then pay for it over the Internet. The seller delivers the goods in physical form or digital. Individuals and businesses from other countries use e-commerce platforms for payment and settlement transactions, and items are delivered through the international logistics system [1]. It is referred to as CBEC. CBEC suppliers and customers can use the Internet to sell and acquire products all over the world. As a result, transaction expenses like communications, market research, and administration are significantly reduced. CBEC is popular in developing countries because it helps exporters overcome barriers such as a lack of information, isolation from potential markets, and high market entry costs [2]. In recent years, China’s imported cross-border e-commerce has shown exponential growth too. This is due to the rapid growth of domestic overseas shopping users, the increasing public trust in overseas brands, the upgrading of consumption concepts, and the diversification of demand. At the same time, the government’s incentive measures in cross-border finance, taxation, and logistics have also created favorable conditions for the development of imported cross-border e-commerce. In 2020 global cross-border e-commerce market transactions, China’s transaction amount was 3.24 trillion Yuan [3]. However, domestic cross-border import e-commerce has also switched from the purchasing agent and overseas shopping model to the 3.0 cross-border import model. Transnational consumption has become regulated; thus, more users have begun to purchase products from other countries through imported cross-border e-commerce channels. For this reason, with the growth of global demand, transnational online shopping has become an important way for people to consume on the Internet platform [4]. Tmall International, NetEase, Vipshop, and http://JD.com/ seized good opportunities to enter the cross-border shopping market, and the multinational e-commerce market developed rapidly [5, 6].
2. The Status quo of Cross-Border E-Commerce in the Context of Cultural Differences

This section explains the barriers to cultural exchange, easy to misunderstand, and customer's resistance. It will help understand the status quo of cross-border e-commerce in the context of all the cultural differences that come in the way of cross-border e-commerce.

2.1. Barriers to Cultural Exchange. One of the major barriers that come in the way of cultural exchange is the language. In many cases, whether it is exporting cross-border e-commerce customer service or customers, they are not using their native language in the communication process. In the process of language conversion, there are situations such as untimely replies and improper use of words. This may have an impact on the communication between the two parties [18, 19]. In addition, some export cross-border e-commerce customer service and customers will use network translation software in the communication process [20]. However, in many circumstances, the translation of translation software is not authentic, causing the sentence's original meaning to be lost. This sometimes results in the export of cross-border e-commerce customer service [9, 21].

2.2. Easy to Misunderstand. Part of the export cross-border e-commerce customer service, in the process of replying to customer emails, is used to using paragraphs of capital letters, sometimes marked with more eye-catching colors to highlight their key points [22]. However, under different cultural differences, the use of word marks will create misunderstandings among the people. There is a possibility that the customer will think it is an act of abuse or insult. If such emails are seen by customers, then customers will think that they have not received the respect they deserve. Export cross-border e-commerce customer service uses this response method, mainly to allow customers to immediately notice keywords and help customers understand specific content [3, 23]. However, cultural differences will inevitably lead to misunderstandings by the other party. It will lead to conflicts between the two parties without knowing it. In the process of communicating with customers, export cross-border e-commerce customer service will use some of the more accustomed expressions of the country. For example, use polite language to show respect for customers. However, simple and direct language is preferred by Western customers. They would believe that the customer service is avoiding the problem and does not want to aggressively fix the problem if they employ courtesy comments in the communication process, causing tremendous difficulties for both sides [21, 24, 25].

2.3. Customers Have Resistance. During export cross-border e-commerce transactions, customers will only communicate with customer service after purchasing goods and discovering problems with the goods. In cross-border export transactions, customers often communicate with customer service because of the contrast between the physical object and the picture, product quality problems, quantity inconsistency, and packaging problems. Usually, this kind of situation will confuse the customers. There will be dissatisfaction with the work of customer service. Due to cultural differences, time lag, and other factors, the customer service cannot answer customer questions in time or can answer customer questions quickly, but the content of the reply cannot be understood by the customer. The occurrence of this kind of situation will cause serious resistance to customers and a lack of patience. This in turn causes a lot of unnecessary troubles to the normal operation of the customer service platform [26]. Differences in culture arise from regional similarities and differences, as well as cultural similarities and differences specific to people in different places. Hofstedt essentially
divides cultural differences into four dimensions: power distance, uncertainty avoidance, masculinity, and collectivism. Gefen Heart pointed out that trust is generated by cultural differences. Research by Lim also shows that people in different cultural backgrounds have inherent differences in building trust. It influences the relative effectiveness of online shopping strategies. Compared to the traditional commercial trade, e-commerce trade has shortened the distance between person-to-person transactions to a certain extent, enabling transactions to be completed in a short time, and greatly saving transaction time and costs [27]. Therefore, different cultural differences bring great convenience to consumers for business activities and promote healthy cultural exchanges. The impact of behavior will start to affect consumers’ trust in cross-border e-commerce. Vyncke and Brengman (2010) pointed out that e-commerce websites with cultural consistency can better adapt to potential consumers from different cultures, and thus have higher website effectiveness. It brings a better experience to consumers, creating a sense of trust invisibly [28–30].

Consumers will have “distrust” of orders placed on the cross-border e-commerce platform due to cultural differences. It has caused many unnecessary troubles in the operation of the platform. For this reason, enhancing the trust of the platform has become a major issue. When customers consume on the platform, they all hope to buy their satisfactory products from the platform, and the platform can provide satisfactory services so that consumers have a sense of trust in the platform. For customers, how to distinguish whether the platform is trustworthy involves effective evaluation under different cultural differences. This research attempts to start from the influencing factors of cross-border e-commerce platform trust, establish a scientific evaluation model and evaluate it, and provide a reference for consumers to better realize cross-border e-commerce shopping under the conditions of cultural differences, promote the orderly development of cross-border e-commerce [31, 32].

3. Establishment of Credit Evaluation Model

This section explains the random forest model, AdaBoost Integrated Learning Model, and Bagging Integrated Learning Model. It will help to establish a credit evaluation model for the end consumer as well as for the supplier.

3.1. Random Forest Model. Random forest uses decision tree as its base classifier. It is a strong classifier composed of multiple decision trees. Its basic premise is based on the idea that as the number of trees in a random forest grows, numerous decision trees vote to select the most credible result, improving generalization errors convergence and overall accuracy. Specifically, given a sample set, randomly sample from the sample set A to obtain a set of classifiers \( h_1(x), h_2(x), \ldots, h_k(x) \), for the random variables \( X \) and \( Y \) in the sample, the expression of the margin function is:

\[
mg(X, Y) = av_k I(h_k(x) = Y) - \max_{j \neq k} av_k I(h_k(x) = Y).
\]  

Among them, \( I(\bullet) \) is the indicator function. The function of the limit measures the degree to which the number of votes received by the randomly selected samples exceeds the number of votes received by the incorrectly sampled. The greater the value of the margin function, the more reliable the result of the prediction obtained by the inactive forest. The effects of generalized forest deforestation are presented as:

\[
PE^+ = P_{X,Y}(mg(X, Y) < 0).
\]  

Describe a mixed image of an indescribable forest as \( h_k(x) = h(X, \Theta_k) \). According to the strict rule of thumb, in sequence \( \Theta_1 \ldots \Theta_k \), as the undefined forest continues to grow, the effects of generalization will continue to occur:

\[
P_{X,Y}(h(X, \Theta) = Y) - \max_{i \neq j} P_{X,Y}(h(X, \Theta) = j < 0).
\]  

The random forest generalization error’s continuous convergence indicates that the approach will not cause the model to overfit due to the tree’s continuous development, but there will be some generalization error.

3.2. AdaBoost Integrated Learning Model. The AdaBoost algorithm can be explained and deduced through the continuous iteration of the additive model and the continuous optimization process of the exponential loss function. There is a problem with inserting binaries. For example, training set \( \{(x_1, y_1), (x_2, y_2) \ldots (x_m, y_m)\} \), let the actual work be \( f(x) \), and the combination of the undergraduate student’s work line is \( H(x) = \sum_{t=1}^{T} \lambda_t h_t(x) \). Based on the initial probability distribution \( D_t \) of the sample, the exponential loss function is:

\[
\Phi \exp(\omega_t h_t / D_t) = e^{-\omega t} (1 - \varepsilon_t) + e^{-\omega t} \varepsilon_t.
\]  

If the exponential loss function can be minimized, the classification error rate will also be minimized, and the loss function will be minimized. This means that \( \text{sig}(H(x)) \) can obtain the Bayesian optimal error rate. Therefore, subtracting the results of the exponential loss and creation from 0, we find:

\[
\omega_t = \frac{1}{2} \ln (1 - \varepsilon_t)/\varepsilon_t.
\]  

Formula (5) is the weight for improving the formula of the AdaBoost algorithm. This means, in repeating algorithm patterns, the base learner generated by a certain round of iteration can correct the prediction error generated by the previous round of base learner, that is, the base classifier generated by each sample set can minimize the classification error, thereby minimizing the loss function of the final AdaBoost model. Then, according to \( D_t \) and \( D_{t+1} \), the updated formula for the sample distribution is:

\[
D_{t+1}(x) = D_t(x) e^{-\omega_t f(x)h_t(x)} / Z_t.
\]
Table 1: Confusion matrix.

<table>
<thead>
<tr>
<th>Actual value</th>
<th>Response</th>
<th>Predictive value</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Real case (TP)</td>
<td>False negatives (FN)</td>
<td>Real case (TP) + false negatives (FN)</td>
</tr>
<tr>
<td></td>
<td>False positives</td>
<td>True negative (TN)</td>
<td>False positives + true negative (TN)</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>False negatives (FN) + true negative (TN)</td>
<td>Real case (TP) + false positives + false negatives (FN) + true negative (TN)</td>
</tr>
</tbody>
</table>

Among them, \( Z_t \) is the normalization factor. The final output function formed by AdaBoost is:

\[
H(x) = \text{sign} \left( \sum_{t=1}^{T} \omega_t h_t(x) \right). \tag{7}
\]

3.3. Bagging Integrated Learning Model. Assuming that the prediction function \( \Phi(X, L) \) is obtained through the training set \( L = \{ (y_n, x_n) \} \), the Bagging algorithm uses a series of mutually independent and identically distributed data sets \( \{ L_k \} \) generated by \( L \) to obtain a better prediction model standard than the prediction model \( \Phi(X, L_k) \). A large number of independent and identically distributed data sets \( \{ L_k \} \) are generated by \( L \) to generate the Bagging algorithm, thereby generating the final predictive model \( B \) generated for a single learning set. The Bagging model applied to classification will generate a classification model for each data set \( \{ L_k \} \), that is, each quasi-\( \Phi_B(x) \) of \( \Phi_B(x) = \text{avg}_k \Phi(x, L^{[B]}_k) \) forms the final prediction model through continuous voting. In a retrospective study of the structure of the data set \( \{ L_k \} \), it may be predicted the outcome of each \( \Phi_B(x) \) stable determinant of the Bagging mode.

Define the Bagging model as \( \Phi(x) = \arg \max_j Q(j|x) \). Depending on the task, the potential for real classification is:

\[
\sum_j I(\arg \max_r Q(r|x) = j) P(j|x). \tag{8}
\]

where \( I(\bullet) \) is the indicator function. From the perspective of orderly correction, the Bagging model can get the total classification accuracy rate, which is expressed as:

\[
\text{rate} = \int_{C} \max_j jP(j|x)PX(dx) + \int_{C'} \left[ \sum_j I(\Phi(x) = j) P(j|x) \right] PX(x). \tag{9}
\]

Here, \( C \) is the default \( x \) setting set, and \( C' \) is its helper. From this, it can be found that the orderliness of a single set of data may not be the best in a structured system, generated by a single data set may not be the best in an orderly correct set, but the Bagging model \( \phi(x) \) can achieve the best classification accuracy.

Table 2: Model evaluation indicators.

<table>
<thead>
<tr>
<th>Index name</th>
<th>Calculation formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy rate, AR</td>
<td>( \text{AR} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} )</td>
</tr>
<tr>
<td>True positive rate, TPR</td>
<td>( \text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} )</td>
</tr>
<tr>
<td>False positive rate, FPR</td>
<td>( \text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} )</td>
</tr>
<tr>
<td>False negative rate, FNR</td>
<td>( \text{FNR} = \frac{\text{FN}}{\text{TP} + \text{FN}} )</td>
</tr>
</tbody>
</table>

4. Model Evaluation Index

The classification model of machine learning methods has some important evaluation indicators, such as confusion matrix, KAPPA statistics, and AUC. Confusion matrix is shown in Table 1. According to the result of the confusion matrix, the evaluation index of the model can be calculated, as shown in Table 2.

Here, AUC (area under ROC curve) is defined as the area under the ROC curve and coordinate axis. ROC curve (receiver-operating characteristic curve) considers false positives as abscissa and true facts as planned. Different points are connected into a curve. The Kappa statistic is calculated based on the confusion matrix, which measures the degree of difference between the random forest model predicted classification results and the random predicted classification results, and its value is between \([-1, 1]\). In practical applications, the general value is \([0, 1]\). If the Kappa statistic is 0, it means that the prediction result of the random forest model is the same as the random prediction result, and the model has no effect. The higher the value of the coefficient, the higher the type of comparison obtained by the model.

5. Empirical Analysis

This section explains the comparison of three ensemble learning models and Validity of Internet Text Data Credit Evaluation. This will help to analyze the empirical analysis of the data that has been gathered.

5.1. Comparison of Three Ensemble Learning Models. This article uses WEKA3 machine learning software to realize the training of three ensemble learning models: random forest, AdaBoost, and Bagging. After experimental testing, the relevant parameter settings are shown in Table 3.

Comparing the results of the three types, which can be seen from the positive measure, true false measure, true measure, Kappa, and AUC numbers of the three types, the wild model works best. Among the results of the final prediction of the random forest model: the true positive rate is...
and H3 is in H2. Join Xracy rate is 92.87%. The Kappa statistic is 0.843. This indicates that the model has a good generality. It can be seen from the importance of the variables in Table 5 that random forest has identified five important variables X1, X2, X3, X4, X5 (current ratio, asset-liability ratio, cash flow debt ratio, inventory-to-income ratio, fixed assets, and income ratio). After joining X20 (risk transparency), the risk transparency variable X20 entered the ranking list of importance and is the tenth important variable. After adding X21 (shareholder confidence) on this basis, the importance of the variable of shareholder confidence ranks eleventh. Therefore, cash flow ratio, asset-liability ratio, cash flow debt ratio, inventory-to-income ratio, and fixed assets-to-income ratio are all important factors for corporate credit evaluation in models H1, H2, and H3. Risk transparency and stockholder confidence variables are added. It will change the importance of variables, which means that the two have played a certain role in the training and verification of the enterprise credit evaluation model.

As shown in Table 6, in the results of the predictors for models H1, H2, and H3, the false positive ratio gradually decreases, and the true positive and negative ratio gradually increases. It indicates that the risk transparency variable X20 and the stockholder confidence variable X21 have an impact on the corporate credit risk. The identification of risk has played a certain role, which in turn shows that the analysis of future business risks in the annual financial report and the text of stockholders’ comments play a certain role in corporate credit evaluation.

6. Conclusion

Using Internet text’s big data to improve the authenticity and accuracy of consumers’ credit evaluations of cross-border e-commerce is an important and unresolved issue. Therefore, this article mainly studies the following issues: it proposed a set of indicators for evaluating corporate credit, including company solvency and desire to repay. These markers were discovered through a survey of the literature and field research. The foundation for quantitative analysis is studied from two perspectives. First, this article used the company’s future business risk’s analysis text and shareholder opinion’s text data from the Internet. The company’s willingness to repay debt is measured using two indicators: risk transparency and shareholder confidence. Next, the random forest model, AdaBoost model, and Bagging model were used to verify the impact of corporate debt repayment willingness on corporate credit evaluation, derive key indicators of corporate credit evaluation, and compare and contrast the performance of the three corporate credit risk evaluation models. Consumer trust is a key factor in the development of cross-border e-commerce. It involves many...
subjects and is very complex. The author believes that the construction of consumer trust is phased. There will be different requirements in each stage. We should analyze the problems specifically and make efforts from different levels such as consumers, businesses, products, and websites to create a good economic environment for the development of cross-border e-commerce. At present, in the process of cross-border e-commerce transactions, unsafe factors have been controlled to some extent, and the frequency of security incidents encountered by Internet users has decreased. It will improve consumers’ trust in e-commerce and platforms. However, building consumer trust is still a long process. To improve confidence and support the development of cross-border e-commerce, the government, consumers, enterprises, and third-party platforms should collaborate.

**Data Availability**

The data sets used and analyzed during the current study are available from the corresponding author upon reasonable request.

**Conflicts of Interest**

The author declares he has no competing interests.

**References**


