

**THE IMPACT OF SOCIAL BUSINESS PLATFORM ON CONSUMER LOYALTY: A
CASE STUDY OF ZHEJIANG FRESHHERMA AS AN EXAMPLE MARKET**

Li-Wei Lin* , Su-Rong Yan and Yu-Xin Teng

Zhejiang University of Finance and Economics Dongfang College Zhejiang ,China

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ABSTRACT

2019 the community business platform in mainland China more and more popular. Mainly because of the functionalities of social business platform innovation, community business links are constantly changing, creating a new business community platform business model. Many scholars have neglected the consumer loyalty of the community in the study community business, the community is through the circle of friends of word of mouth, trust, information transmission, to build consumer loyalty to the community business platform. The number of samples in this study was N = 471, and the impact of the social commerce platform function on consumer loyalty was investigated through investigation. The object of our investigation is to freshherma as the object of investigation, the ultimate goal is to understand their consumer platform for the use of the situation.

Keyword: community commerce, word of mouth, trust, consumer loyalty.

1. INTRODUCTION

The most important part of community business is the relationship between the platform and the consumer. The two-way relationship between the community business platform and consumers, from the transmission of information to the establishment of consumer beliefs and the value of the social business platform, to establish consumer loyalty, which is one of the biggest research factors in this study. . The function of social commerce needs to establish beliefs and status in the minds of consumers. These functions need to be constantly introduced to attract consumers to continue to use their social business platform. Lijander (2000) proposed that consumer loyalty definition is a related factor of product perception and feeling. Therefore, we can understand that the most important key factor of the community business platform is to enable users to clearly understand the use and operation of platform functions, indirectly causing the impact of their consumer loyalty. Zeithaml (1988) proposed that customer perceived value is one of the key factors determining consumer loyalty. Huang Yinghao (2005) proposed that experience marketing should be based on the concepts of senses, emotions, perceptions, etc., to further achieve the trust of consumer loyalty. Grosby (1990) proposed consumer satisfaction as an attitude towards understanding the comprehensiveness of its consumer product offerings.

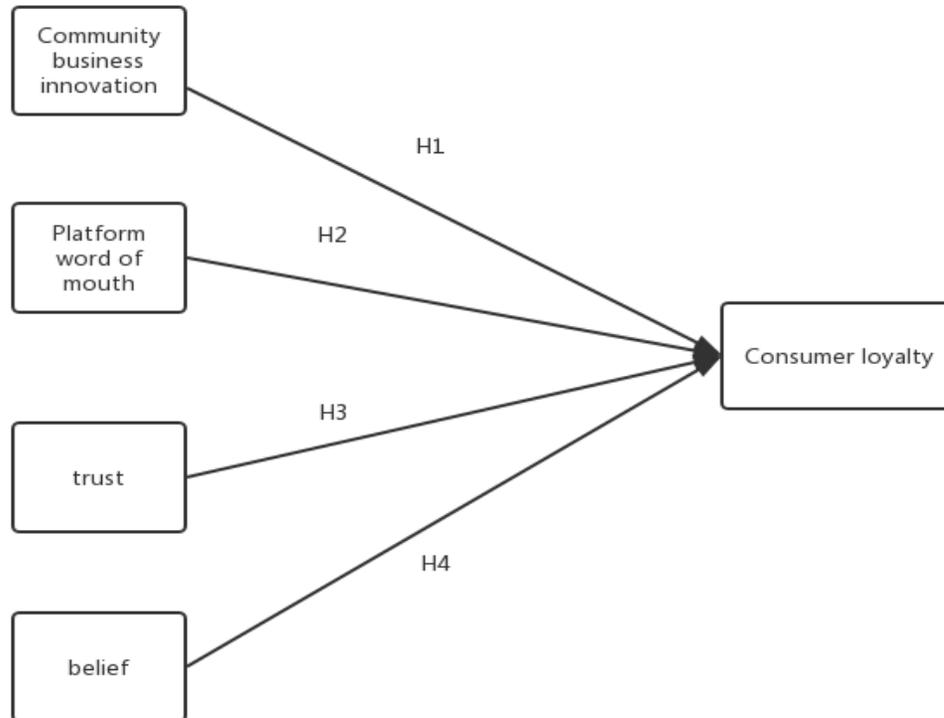
The most important concept of the social platform is to share information, and the importance and authenticity of the information has become one of the most important concepts. The most

important purpose of this research is that the functions provided by the community business platform can correctly transmit information to consumers and further gain the recognition of their consumers. McCarter & Northcraft (2007) suggests that trust comes from the willingness of both parties to share the right information and create the greatest value. Morgan & Hunt (1994) proposed that consumers have higher trust and higher loyalty. Trust is also a key factor in the community business platform, building a relationship between the social networking platform and consumers through trust. The biggest goal of this study is to investigate the functional diversity and innovation of its social business platform, and whether it can have a positive impact on consumer satisfaction.

2. LITERATURE REVIEW

The development of community commerce has seen many community business models in the Chinese market in recent years. For example, the business model on the WeChat platform, from the consumer's WeChat payment, WeChat red envelope, Didi drunk ride mode, is gradually integrated in the consumer's life process. Community business refers to a platform for interpersonal relationships. Through the sharing, evaluation and interaction of Internet users on the Internet, consumers' loyalty to the community business platform is achieved. Wasko & Faraj (2005) proposed that social capital is an interactive way, and members of these networks express their trust, respect and friendship through mutual interaction. Jin et al., (2015) mentioned that the social capital of an individual is mainly through the participation of individuals in social media, and the more social capital they have. Therefore, the most important purpose of these business models of social commerce is to further achieve customer satisfaction through interaction and exchange of information between consumers. Kim & Park (2013) mentioned that credibility, communication, word of mouth and trust will have a certain impact on the delivery of business information to consumers. Zhang et al. (2010) mentioned that online word of mouth can reduce the risk of product uncertainty. These consumers exchange purchase behavior, the ultimate goal is to enable consumers to reduce the risk of their purchases in purchasing behavior, and further to achieve their consumer satisfaction. The main purpose of community commerce is to establish its consumer loyalty, through the transactions of buyers and sellers on the platform, to further achieve the consumer's continuous purchase. Consumer loyalty can be analyzed from information sharing and message on the social platform, through the information exchange on the platform and consumer behavior to observe, to further understand the impact of its community business on consumer loyalty. . The most important thing for a community website is to build the beliefs and beliefs of consumers and further build a reputation for the platform. Word of mouth is a very important concept in marketing. To promote and promote through consumers, the ultimate goal is to establish consumer loyalty. This kind of word of mouth can be reached through the circle of friends or friends to promote the communication of its community business platform. Butner (2008) suggests that consumer trust accounts for a very important factor in community commerce. The function of social commerce will have an important key factor for the future status of the entire consumer in the mind. Through its research architecture design, this study mainly wants to explore the impact of its community business functionality on consumer loyalty.

3. THE RESEARCH MODEL



This study is based on the design of four hypotheses, the main purpose of which is to conduct exploratory research, and hope to verify whether the hypothesis is relevant through the analysis of hypothesis testing. We use hypothetical verification to design whether its community business innovation, platform reputation, trust, and beliefs are relevant to consumer loyalty. The following is a hypothetical test for this study:

H1: Is community business innovation relevant to consumer loyalty?

H2: Is platform word-of-mouth relevant to consumer loyalty?

H3: Is trust related to consumer loyalty?

H4: Is belief related to consumer loyalty?

The main purpose of this study is to test the relevance of the four hypotheses, mainly to discover the impact of its community business platform function on its consumer satisfaction, and the ultimate goal is to find its research contribution.

4. RESEARCH METHODS

4.1 Introduction and comparison of research methods

4.1.1.Discriminant analysis

The difference analysis (or discriminant analysis) is a dependent method, and the criterion variable is a predetermined category or group. The difference analysis analyzes the sample set used to generate the Discriminant Function, called the training set, and another set of samples can be used to predict the group to which the observation belongs, for the purpose of analysis:

- (1) *Find the difference function based on the predictor to distinguish or predict the attribution of the observation.*
- (2) *A linear combination of predictors that best distinguishes differences between groups.*
- (3) *From a set of predictors, find the subset of variables that best distinguish the differences between groups.*

4.1.2.Cluster Analysis

Cluster analysis is to collect observations or variables in the dataset into the same cluster, and can perform Hierarchical Cluster and Non-hierarchical Cluster (Disjoint Cluster). Hierarchical and non-hierarchical cluster analysis is only possible with numeric variables.

Table 1-The two analytical methods are compared, as shown in the following table:

Analytical method	Discriminant analysis	Cluster Analysis
Method description	Dependent method	Division method
Method objective	1. Do similar classifications to make differences 2. Find out the maximum difference in predictor variables 3. Find a linear combination of predictors so that the ratio of variation between groups to the variation within the group is the largest	Classify similar groups of properties
Group characteristics	Have prior knowledge of classification	Classify beforehand completely unknown beforehand

4.2 The data set description and factor analysis review

(1) Using the previous "Investigation of Willingness to Pay for Internet Tax Services", the variables F1 to F8 complete the results of the factor analysis and summarize the following table.

Table 2-the variables F1 to F8 complete the results of the factor analysis and summarize:

Self-variable																									
Data content	The problem of online tax filing services, the willingness of online tax filing services																								
Scaling	converts Non-Metric data to Metric data by Coding mechanism																								
Sample Size	471 pens > 10*28 (variables)																								
Tests for Normality	determines the normal distribution of data according to the Central Limit Theorem (CLT)																								
Suitability test	50% R value >=0.3 passed																								
	Respective MSA>0.5 passed																								
	Overall MSA>0.5 Overall MSA=0.932352 , passed																								
Number of determinants	Select the factor of Eigen value>1 Eigen value > 1, a total of 5 values (additional 1 neighbor value), a total of 6 factors																								
Factor loading	<table border="0"> <tr> <td>variable</td> <td>attribution</td> <td>Factor1</td> <td>e7 e12 e8 e10 e9 e14 e13 e11</td> </tr> <tr> <td>factor>0.3</td> <td></td> <td>Factor2</td> <td>f5 f8 f6 f1 f7 f2</td> </tr> <tr> <td></td> <td></td> <td>Factor3</td> <td>e4 e3 e2 e1 e6</td> </tr> <tr> <td></td> <td></td> <td>Factor4</td> <td>e16 e20 e18 e17 e19</td> </tr> <tr> <td></td> <td></td> <td>Factor5</td> <td>f4 f3 e5</td> </tr> <tr> <td></td> <td></td> <td>Factor6</td> <td>e15</td> </tr> </table>	variable	attribution	Factor1	e7 e12 e8 e10 e9 e14 e13 e11	factor>0.3		Factor2	f5 f8 f6 f1 f7 f2			Factor3	e4 e3 e2 e1 e6			Factor4	e16 e20 e18 e17 e19			Factor5	f4 f3 e5			Factor6	e15
variable	attribution	Factor1	e7 e12 e8 e10 e9 e14 e13 e11																						
factor>0.3		Factor2	f5 f8 f6 f1 f7 f2																						
		Factor3	e4 e3 e2 e1 e6																						
		Factor4	e16 e20 e18 e17 e19																						
		Factor5	f4 f3 e5																						
		Factor6	e15																						
Factor score	<table border="0"> <tr> <td>Factor1</td> <td>$e7*0.27231 + e12*0.26237 + e8*0.24897 + e10*0.25161 + e9*0.21369 + e14*0.17963 + e13*0.11954 + e11*0.06719$</td> </tr> <tr> <td>Factor2</td> <td>$f5*0.29709 + f8*0.24031 + f6*0.27667 + f1*0.22370 + f7*0.24570 + f2*0.24322$</td> </tr> <tr> <td>Factor3</td> <td>$e4*0.39302 + e3*0.38785 + e2*0.27288 + e1*0.25114 + e6*0.14642$</td> </tr> <tr> <td>Factor4</td> <td>$e16*0.39442 + e20*0.29736 + e18*0.27906 + e17*0.27391 + e19*0.31735$</td> </tr> <tr> <td>Factor5</td> <td>$f4*0.44567 + f3*0.34074 + e5*0.29082$</td> </tr> <tr> <td>Factor6</td> <td>$e15*0.82546$</td> </tr> </table>	Factor1	$e7*0.27231 + e12*0.26237 + e8*0.24897 + e10*0.25161 + e9*0.21369 + e14*0.17963 + e13*0.11954 + e11*0.06719$	Factor2	$f5*0.29709 + f8*0.24031 + f6*0.27667 + f1*0.22370 + f7*0.24570 + f2*0.24322$	Factor3	$e4*0.39302 + e3*0.38785 + e2*0.27288 + e1*0.25114 + e6*0.14642$	Factor4	$e16*0.39442 + e20*0.29736 + e18*0.27906 + e17*0.27391 + e19*0.31735$	Factor5	$f4*0.44567 + f3*0.34074 + e5*0.29082$	Factor6	$e15*0.82546$												
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Factor reliability	Cronbach $\alpha > 0.6$ Factor1~5 are greater than 0.6 to meet the reliability test, no sensitivity analysis is needed																								
Factor validity	Convergence validity Factor 1~5 are consistent with convergence validity																								

Differential validity	Factor 1 to 5 are consistent with different validity
Remarks: Factor6 has only one variable and can be used as a factor.	

(2) *The following information is based on the “Investigation of Willingness to Pay for Internet Tax Services”. The variable C2-C48 uses the “Double Numbers” to complete the analysis of the factors and summarizes the following table.*

Table3-complete the analysis of the factors and summariz

Variable	
Data content	The degree to which an individual pays attention to the question (the left half) and the situation that the individual actually feels when performing the online tax return service (right half)
Scaling	converts Non-Metric data to Metric data by Coding mechanism
Sample Size	471 pens > 10*24 (variables)
Tests for Normality	determines the normal distribution of data according to the Central Limit Theorem (CLT)
Suitability test	50% R value >=0.3 passed
	Respective MSA>0.5 passed
	OverallMSA>0.5 Overall MSA=0.95845352 , passed
Number of determinants	Select the factor of Eigen value>1 Eigen value > 1 , with 3 values, A total of 3 factors
Factor loading	variable attribution factor>0.3 Factor1 c4 c14 c2 c16 c6 c20 c12 c8 c10 c32 c18 c34 Factor2 c48 c40 c38 c46 c42 c44 c36 Factor3 c22 c24 c28 c26 c30
Factor score	Factor1 $c4*0.23029 + c14*0.21376 + c2*0.20485 + c16*0.19682 + c6*0.17717 + c20*0.15688 + c12*0.17187 + c8*0.13215 + c10*0.09481 + c32*0.08876 + c18*0.08338 + c34*0.04309$
	Factor2 $c48*0.39108 + c40*0.32192 + c38*0.31743 + c46*0.30007 + c42*0.1886 + c44*0.19072 + c36*0.11598$
	Factor3 $c22*0.41418 + c24*0.37695 + c28*0.31877 + c26*0.26268 + c30*0.22570$

Factor reliability	Cronbach $\alpha > 0.6$	Factor 1~3 are greater than 0.6 to meet the reliability test, no sensitivity analysis is needed
Factor validity	Convergence validity	Factor 1~3 are consistent with convergence validity
	Differential validity	Factor 1 to 3 are consistent with different validity

4.3 The difference analysis process

4.3.1. Sample number test

(1) When performing the difference analysis, the level of the "variable" can be pulled to the "factor". This will affect the condition of the minimum number of samples. The minimum number of samples required for the difference analysis must be at least 20 times the number of IV. There are 6 IVs for this "factor" level, so the minimum number of samples must be $6 * 20 = 120$ or more.

(2) In addition, due to the construction mode and cross-validation requirements, the data set samples are split into Estimate data and Holdout data. Estimate data is at least 120 ($6 * 20 = 120$); as for the Holdout data sample, according to the ratio of Estimate data and Holdout data in 5:1 ($471 / 6 = 78.5$, based on 80), which means Holdout The data needs to be greater than 80 pens to meet the threshold of the sample number.

(3) The research data was distributed in a 6:4 ratio. Estimate data = 282 > 120 (minimum number of samples), and holdout data = 189 > 80 (sample 5:1 allocation), both of which meet the minimum sample requirement.

Sample segmentation	minimum judgment	sample number	number	criteria	is greater than the minimum sample number
The total number of samples is 471	$6 \text{ (variable)} * 20 = 120$			YES	
Estimate data : 282	$6 \text{ (variable)} * 20 = 120$			YES	
Holdout data : 189	$471 \text{ (sample)} / 6 = 78.5 \text{ (based on 80)}$			YES	

(4) Data conversion. The DVs adopted in this study select "convenience" as the explanatory variable DVI, and DVI uses 7.8 as the data conversion benchmark: if the observed value is less than 7.8, the conversion data is set to 0; if it is greater than 7.8, the conversion data is set to 1.

4.3.2. Assumption Test

(1) Use the Shapiro-Wilk test to check if the variables are normally assigned. The results of the verification are as follows:

variable	Test Value	Statistic	P Value	result
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DV1	Shapiro-Wilk	W	0.944173	Pr< W	< 0.0001	rejected
IV1	Shapiro-Wilk	W	0.992943	Pr< W	0.2065	accepted
IV2	Shapiro-Wilk	W	0.98323	Pr< W	0.0022	rejected
IV3	Shapiro-Wilk	W	0.981001	Pr< W	0.0008	rejected
IV4	Shapiro-Wilk	W	0.989563	Pr< W	0.0421	rejected
IV5	Shapiro-Wilk	W	0.981447	Pr< W	0.0010	rejected
IV6	Shapiro-Wilk	W	0.940225	Pr< W	<0.0001	rejected

It is known from the above table that the IV1 normal distribution result is accepted. Therefore, the probability distribution model of the parent is not normal distribution and cannot meet the basic assumption of difference analysis. However, based on the central limit theorem, when the sample size is $n \geq 30$, the number of samples is $471 > 30$, so the sample average distribution is normally assigned.

(2) Test Homogenous of Variance

Homogenous can be measured by the chi-square test value. If the value is greater than 0.05, Variance is homogenous. It is known from the above figure that the value is less than 0.0001, that is, Variance does not conform to homogeneity.

4.3.3. Multivariate Collinearity Test (Test of Multi- Collinearity)

(1) Using the correlation matrix to detect collinearity, the criterion is judged: if the R value is greater than 0.9, it means that there is collinearity. Observe that the R values in the table below are not greater than 0.9, indicating that they are not collinear.

Total sample correlation coefficient / Pr> r						
variable	IV1	IV2	IV3	IV4	IV5	IV6
IV1	1					
IV2	0.59119 <.0001	1				
IV3	0.62347 <.0001	0.60153 <.0001	1			
IV4	0.4352 <.0001	0.56267 <.0001	0.5574 <.0001	1		
IV5	0.4494 <.0001	0.36375 <.0001	0.22569 0.0001	0.20579 0.0006	1	
IV6	-0.00516 0.9317	-0.13668 0.0226	-0.13833 0.0211	-0.13832 0.0211	0.15278 0.0107	1

(2) Tolerance (TOL) and Variance inflation factors (VIF) are used to detect whether there is a strong correlation between the variables of IVs, but exist in the collinearity problem. If the test standard is $TOL < 0.1$ or $VIF > 10$, there may be a collinearity problem. The collinearity test was performed for IV, and the results are shown in the following table.

Test variable	Other variables	TOL	VIF	collinearity
IV1	IV2	0.51402	1.94543	No
	IV3	0.56642	1.76547	
	IV4	0.6064	1.64907	
	IV5	0.82527	1.21172	
	IV6	0.92596	1.07996	
IV2	IV1	0.50447	1.98229	No
	IV3	0.50005	1.99981	
	IV4	0.66846	1.49597	
	IV5	0.76888	1.3006	
	IV6	0.935	1.06952	
IV3	IV1	0.57092	1.75157	No
	IV2	0.51356	1.94717	
	IV4	0.66103	1.5128	
	IV5	0.75091	1.33172	
	IV6	0.9269	1.07886	
IV4	IV1	0.47414	2.10909	No
	IV2	0.53256	1.87771	
	IV3	0.51278	1.95015	
	IV5	0.74118	1.3492	
	IV6	0.92459	1.08156	
IV5	IV1	0.52762	1.8953	No
	IV2	0.50088	1.99649	
	IV3	0.4763	2.09952	
	IV4	0.60605	1.65004	
	IV6	0.9549	1.04723	
IV6	IV1	0.47612	2.10031	No
	IV2	0.48988	2.04132	
	IV3	0.47285	2.11482	
	IV4	0.60803	1.64464	

IV5	0.76799	1.3021
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4.3.4.Prediction Efficiency

(1) Z statistic

H0: Centroid 0 = Centroid 1. The verification result is <0.0001, Reject is assumed (H0), so the Overall model is established.

(2) ANOVA (based on Zignificant)

After the above overall model is established, each variable is further tested individually, as shown in the following table:

Verification hypothesis: H0: = ... and so on to IV6, hope that the variable has the ability to distinguish, so expect Reject (P value <0.05). The verification results: the P values of the variables IV1~IV5 are all less than 0.05, indicating that the variables have the ability to distinguish. In addition, among the 1 group and the 0 group, the most different variables (the farthest away from the variable) are observed, and the F value data is the largest. The most distinguishing ability. According to the IV4 variable (F value = 73.24), the most distinguishing ability.

(3) Cutting Score

The Z (score value) generated by the data is used to identify the group's attribution by the Cutting Score.

If it is Equal group sample size
$$\frac{Z_a + Z_b}{2}$$

If it is Unequal group sample size
$$\frac{N_a Z_a + N_b Z_b}{N_a + N_b}$$

The sample data of this analysis is divided into two groups of "1 group" and "0 group". The number of samples is 186 and 92 respectively. Therefore, the Unequal group sample size calculation method is adopted. The results are as follows:

Cutting score = (186 *0.40229 + 92*(-0.81332)) / (186 + 92) = 1.7985

4.3.5.ClassificationMectric

To find out the error caused by the sample data classified by Discriminate Function (DF), it means that the original sample data itself has no errors, but the error caused by the DF classification and the actual situation.

As shown in the table below, there are 11 observations that were originally classified as "zero group" and "group 1". The original observation value of "1 group" was divided into "zero group" by 37, (yellow block is The correct classification of the data).

Number and percentage of observations classified as Transform			
From Transform	0	1	total
0	81	11	92
	88.04	11.96	100
1	37	149	186
	19.89	80.11	100
total	118	160	278
	42.45	57.55	100
Prior value	0.5	0.5	

(1) *Posterior Probability of Membership in transform:*

In the above, there are 48 (11+47) data, which are classified by DF (marked by "*"), and the error data is as follows:

(2) *Hit Ratio and Cpro*

The following formula shows: Hit Ratio = 0.8273 is greater than Cpro = 0.5571, and the Hit Ratio of Table DF meets the requirements.

Hit Ratio: =0.8273

Cpro: $2 \times 2 = 0.5571$

4.3.6. The most important discriminator

(1) *Discriminant Loading: Explore the relationship between variables and DF. The benchmark is as follows:*

Discriminant Loading > 0.3, table variables have the ability to distinguish, less than 0.3, no significant difference

Discriminant Loading > 0.45, table variables have a "strong" distinction

This study analyzes 6 IVs, and the discriminate Loading is summarized as follows:

variable	Can1	Meethe criteria	judgement result
IV1	0.515999	>0.45	Strong discriminating ability

IV2	0.749407	>0.45	Strong ability	discriminating
IV3	0.750564	>0.45	Strong ability	discriminating
IV4	0.919795	>0.45	Strong ability	discriminating
IV5	0.249132	<0.3	Nosignificant difference	
IV6	-0.344495	<0.3	No difference	significant

(3) *Discriminant weight: The coefficient that constitutes the difference equation. The largest coefficient is the greater the contribution of the table.*

From the following table, it can be seen that the coefficient of IV4 is the largest in the variable group, and the contribution is also the largest.

Total sample normalization coefficient	
Variable	Can1
IV1	-0.106582264
IV2	0.276784691
IV3	0.313440229
IV4	0.734560674
IV5	0.045864475
IV6	-0.221274749

Difference equation: $Z= -0.1065*IV1 + 0.2767*IV2 + 0.3134*IV3 + 0.7345*IV4 + 0.0458*IV5 + -0.2212*IV6$

4.3.7.Prediction Accuracy

(1) *Holdout data sample size*

The number of samples of Holdout data is allocated in a 5:1 ratio according to Estimate data and Holdout data. Therefore, at least 80 (471/6=78.5, based on 80) of the above data should be included in "0 group" plus "1 group". The following figure shows that it meets the sample requirements of holdout data.

(2) *Hit Ratio*

Discrimination: Hit Ratio (holdout data)>1.25* Cpro (estimate data) with cross validity.

Number and percentage of observations classified

as Transform			
From Transform	0	1	total
0	50	4	54
	92.59	7.41	100
1	27	105	132
	20.45	79.55	100
total	77	109	186
	41.4	58.6	100
Prior value	0.5	0.5	

Hit Ratio: $\left(\frac{50+105}{186}\right)=0.8333$

$1.25 \times Cpro: 1.25 \times \left(\frac{92}{278}\right)2 \times \left(\frac{186}{278}\right)2 =0.6963$

The judgment result is $0.8333 > 0.6963$, Hit ratio $> 1.25 * Cpro$, and DF has cross-validity.

5. CONCLUSIONS AND RECOMMENDATIONS

This study can find that cross-border flexibility mechanisms and consumer perception have a significant impact on business model performance. Therefore, we can clearly understand that the cross-border flexibility mechanism and consumer perception will directly affect the business model performance of the entire platform. Therefore, we clearly understand that Hypothesis 1 has a significant relationship with Hypothesis II.

We can therefore get the results of the entire data through SAS software, and we can clearly see the causal logical relationship. Through such a coherent design, we can see whether the correlation is true. The number of samples in this study is N=173, and the correlation is seen by collecting the number of samples. Our ultimate goal is to validate and model the entire model through the establishment and analysis of such a hypothetical model.

We are designing its research structure, content, and methods through the entire rigorous design, and ultimately hope to produce an analysis of the results of this research hypothesis. The biggest contribution of this research is to fill in the research related to cross-border e-commerce. Cross-border e-commerce is a new research field. So far, no one has studied related topics in academic circles. Most of the research on e-commerce is mainly about the functional and application of its platform, and our research is a combination of cross-disciplinary research, such as the combination of psychology, behavior, and international trade. The ultimate goal of our research design hopes to be innovative in cross-border e-commerce research, mainly in the study of cross-border e-commerce mechanisms, consumer perception of business performance model establishment.

The biggest limitation of this research is that it only targets the e-commerce market in Ningbo, China. Cross-border e-commerce is a very important problem in the flow of gold and logistics. If you want to include the markets of other countries, you need to have human and material resources. Very challenging. The cross-border e-commerce research of this study mainly cooperates with the mainland China government's One Belt and One Road policy to conduct research, and has innovative research in e-commerce.

Research implications

The purpose of this research is to respond to whether its community business innovation, platform reputation, trust, and belief have a gap in consumer loyalty. Now the research on social commerce rarely studies the consumer satisfaction of its social business platform. Investigation.

(1) The impact of the functionality of the community business platform was confirmed through this study. That is to say, the social commerce platform has its influence on cross-consumer satisfaction. The main questionnaire distribution object of this study is to investigate the consumer satisfaction of the Haining community business platform market in mainland China, but in the investigation process. Consumers are using the social networking platform to create uncertainty. We suggest that future research can be conducted to expand its survey in East China, not only to investigate its Haining area, so it will be objective and reduce its error in the questionnaire survey.

(2) We further discover that the trust of the community business platform will have an impact on consumer satisfaction. Our research is mainly aimed at the beliefs and trusts of some community business consumers. It can be found that their community business platform will have a significant impact on consumer satisfaction.

(3) The results of this study can also be provided to subsequent researchers for extended discussion and analysis. It is recommended that future researchers can investigate consumers in East China. Although we are surveyed by consumers in Ningbo, after all, because of the regional relationship, there is no way to directly investigate the situation of other consumers in East China using community business.

The practical implications

The research in this paper can respond to the current situation of the community business platform and the promotion of consumer satisfaction. First of all, this study is a small number of concepts that will study the functions of its community business platform. Factual research in the world rarely studies the concept of a community business platform. The Haining community business platform has developed rapidly in recent years, and in line with the policy of the Chinese government community platform innovation, it is constantly growing and innovating.

The future research direction

It is recommended that follow-up researchers can build their innovative variables in the design research structure. This research has made preliminary design and planning investigations in the field of new cross-border e-commerce, because of the lack of human and material resources. The impact of financial resources, there is no way to conduct in-depth investigations and discussions.

In the course of the study, there are two main limitations. The first point is that collecting consumer data on community commerce in the Haining area has its difficulties, because it is not known whether the answer to the consumer survey is correct during the investigation. The second point is that the functionality of the social business platform can be innovative in the future, because the platform is constantly improving and innovating, mainly because of the rapid changes in the market to design and research, it is recommended that follow-up researchers can be more rigorous to design its innovation point variables.

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