Factors Affecting the Consumers Online Shopping During the COVID-19 Pandemic in China

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Abstract
With the spread of the COVID-19 pandemic in China, online shopping became the first choice of consumers. Therefore, the main purpose of the study is to identify the major factors affecting the consumers online shopping during the COVID-19 pandemic in China. In this paper, a binary regression logit model was utilized to measure the key factors influencing consumers online shopping among the Chinese residents. Subsequently, this paper carried out an empirical analysis with the corresponding survey data. The results showed that, the major factors such as service quality, commodity prices, and online shopping experience that affect online shopping in normal social background were insignificant in this pandemic. Interestingly, the contactless service characteristics of online shopping, the shutdown of offline shopping channels, the opinions of people around about the pandemic situation, the pandemic-related official information, and the public panic caused by the pandemic become key influencing factors of online shopping. Based on this, this paper proposed that while taking advantages of the industry benefits brought about by the pandemic, e-commerce companies should not use the public panic to drive up commodity prices and disrupt the market, and meanwhile must pay attention to the maintenance of customer loyalty after the pandemic. On the one hand, while taking measures like shutting down cities and blocking roads to prevent the pandemic, relevant government departments should guarantee the normal operation of logistics, especially those closely related to daily necessities. On the other hand, it is necessary to strengthen the protection of the vital interests of the people, crack down hard on those who deliberately drive up commodity prices and disrupt public order, so as to consolidate the achievements of the fight against the pandemic.
Keywords: COVID-19 pandemic; Online shopping; Logit regression model; Factors; China.

1. Introduction

With the advancement of e-commerce, China is becoming the world's leading online retailer with the highest online shopping growth in the world. Now, the Chinese spend more time online and shop better online. With the boosts in the Internet economy, online shopping has become an important shopping channel for increasing consumers. Therefore, it can said that online shopping is expanding significantly among Chinese consumers as a widespread modern channel driven by high number of internet users. In this regard, many scholars at home and abroad have conducted extensive and in-depth research on the key factors affecting consumers' online shopping from different perspectives. For example, some scholars have found that consumers' online shopping behavior is subject to product scarcity[1-4], perceived value[5], perceived service quality[6-7], risk perception[8-9], shopping experience[10], perceived usefulness[11], consumer's gender[12-17], educational level[18-20], commodity prices[21-24]etc. These confirmed conclusions not only enrich the theories related to consumers' online shopping, but also provide a scientific basis for the online operations of many businesses. But almost all relevant studies focused on the factors that influence consumers' online shopping behavior/willingness under normal social background, few of them were carried out under

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abnormal background. Nevertheless, the frequent occurrence of unconventional events in recent years such as the SARS pandemic in 2003, the H1N1 influenza in 2009, and the ongoing COVID-19 pandemic has become one of the important factors influencing the normal work and life of the general public.

The first case of severe pneumonia with an unknown cause was reported in early December 2019 in Wuhan, the capital of Hubei Province, China. Later, on 9 January 2020, the unknown causative agent was identified as a novel virus in the coronavirus family (ECDC 2020) by the Chinese Center for Disease Control and Prevention (CCDC) [25, 26]. Subsequently, it was listed as an international public health emergency on 30 January 2020 and finally declared a pandemic on 11 March 2020 [27]. To date, over 13 million cases and 570,000 deaths have been reported worldwide since 15 July 2020 [28]. Prior to March 2020, Wuhan city of China [29] had the largest number of cases. In response to the COVID-19 outbreak, the Chinese government in January 2020 enforced several precautionary measures, including lockdown of major cities, stringent health screening, travel restrictions and home quarantine [30].

The ongoing pandemic of COVID-19 has exerted a significant impact on the normal operation of China due to its sudden, highly infectious and latent characteristics. During the pandemic, the Chinese government urged residents to “stay at home and not go out.” The public actively responded to the call of the state for health reasons. In February 2020, 33.8% of the residents went out once every 2-3 days, 30.2% went out once every 4-5 days, 15.8% hardly went out, and about 20% went out every day, according to iResearch [31]. Fighting against the COVID-19 by staying at home became a major feature of this pandemic. This pandemic has inflicted heavy losses on most industries, except for some online industries, which have obtained favorable development opportunities. For example, long videos, short videos, online games, online education, etc. are the few industries with a positive consumption index in this pandemic. However, it is still unknown that the key factors that led the consumers to buy from online in this pandemic, and the similarities and differences between these influencing factors and those under normal social background.

Thus, this paper, under the research background of the ongoing COVID-19 pandemic, takes the factors influencing the online shopping behavior during the pandemic as the research object, and combines the characteristics of the pandemic with the relevant principles of the random utility model to construct a mathematical model of the key factors affecting online shopping in the pandemic and the corresponding scale. With the spread of the COVID-19 pandemic in China, online shopping became the first choice of consumers. Which factors caused the general public to shop online in this abnormal context? Whether these factors are different from those affecting online shopping under normal social background? To find the answers to the questions, this paper, combined the relevant principles of Logit regression model with the characteristics of this pandemic to construct a mathematical model of the key factors affecting online shopping in the pandemic and the corresponding scale. Based on the data obtained from the survey, the influencing factors in the model are verified in a purpose to scientifically and objectively reveal the key factors that cause the public to take online shopping as the main consumption pattern in this pandemic, and the impact of these factors. Therefore, the main purpose of the study is to identify the major factors affecting the consumers online shopping during the COVID-19 pandemic in China. In addition, this paper is also aims to provide a certain reference for the operation of e-commerce companies in this pandemic or in other similar unconventional events, and to provide the necessary decision-making basis for the crisis management of relevant government departments.

The remainder of paper is structured accordingly. Section 2 explains methods selection, model construction, variable selection and scale design. The next section will be followed by the empirical investigation, result and discussion. The paper concludes by discussing its implications, limitations, and future research directions.

2. Research Methods and Model Constructions

2.1 Methods selection

In view of the highly infectious characteristics of the COVID-19, the majority of residents responded to the Chinese government’s appeal for fighting against the COVID-19 pandemic by staying at home. During this period, online shopping became the main shopping channel for the public. The survey results showed that a vast majority of the respondents, 77.24%, said that they would choose to shop online in this pandemic. This paper sets Y as a double-value variable (0 and 1) for people’s choice of shopping methods in the COVID-19 pandemic, among which 1 means that they will choose online shopping in this pandemic, and 0 means not. Meanwhile, it was also found from the survey that, similar to the online shopping in normal situations, the factors leading to the choice of online shopping in this pandemic were various, for example the non-contact service characteristics of online shopping. In addition, these features herein are denoted by X_1, X_2, and X_N respectively.

Since the dependent variable Y is set as a binary random variable in this paper, it is neither possible to use a multivariate linear regression model, nor to directly use the least square method to estimate the model. The Logistic regression model is mainly used to study the probability of certain phenomena, such as the rise or fall of stocks, and the probability of a company's success or failure, and to discuss the factors related to the probability. Given that this paper intends to investigate the key influencing factors that cause the general public to choose online shopping during the COVID-19 pandemic, and the impact of these factors, the Logistic model is thus adopted.

2.2 Model construction

Let the probability of dependent variable Y being 1 be P, then the probability of $Y=0$ is $1-P(0 \le P \le 1)$. To further investigate the correlation between the probability P and the independent variable, the natural logarithm of $\frac{P}{1-P}$ is obtained to be $Ln\frac{P}{1-P}$, recorded as $\operatorname{Logit} P$. Then the logarithm ranges with in $(-\infty, +\infty)$. Here $\operatorname{Logit} P$ is a dependent variable, then the independent variable $x=(x_1, x_2, \cdots, x_k)^T$, and the observation data of n groups are denoted by $(x_{i1}, x_{i2}, \cdots, x_{ik}, y_i)$, where $i=1,2,\cdots,n$. Let $X_i=(1, x_{i1}, x_{i2}, \cdots, x_{ik})^T$, then the Logistic regression model of y_i and $x_{i1}, x_{i2}, \cdots, x_{ik}$ is:

$$\operatorname{Logit} P = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + ...+ \beta_N\chi_N$$

(1)

The logarithm of both sides of this model is obtained as follows:

$$P = \frac{EXP(\beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \cdots}{1 + EXP(\beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + .}$$

(2)

In model (2), the dependent variable Y is a binary variable which only takes the value of 0 or 1, and the probability $P(y=1|X)$ that the dependent variable takes 1 is the object of the model. $X=(1, x_1, x_2, \cdots, x_k)^T$, where x_i is the *i*-th factor that impacts Y.

Since the error form of the discrete variables in the Logistic linear regression model obeys Bernoulli distribution rather than normal distribution, there is no normality assumption. At the same time, the variance of the binary variable is not a constant and has heteroscedasticity. Different from the least squares estimation rule of multiple linear regression (the minimum residual sum of squares), the nonlinear feature of Logistic transformation uses the method of maximum likelihood estimation to find the best regression coefficient. Therefore, the standard for evaluating the degree of fitting of the model is the likelihood value rather than the sum of deviation squares. This paper will use SPSS22.0 for modeling and conduct empirical analysis based on the corresponding survey data.

2.3 Questionnaire design and data collection

This survey had drawn on the relevant rules of Churchill et al., (Churchill& Lacobucci, 2006) and others on questionnaire design. First, a preliminary draft of the questionnaire was formed based on relevant literature and the characteristics of the COVID-19 pandemic. Nine experts (including three scholars in the field, three Internet users and three e-businessmen) were invited to evaluate the questionnaire from the perspectives of intelligibility and representativeness and put forward suggestions for revision. The questionnaire was revised accordingly, which was then fed back to the nine experts for the further review. The final draft of the questionnaire was formed based on the secondary feedback. This questionnaire is divided into two parts: the basic attributes of the respondents, and the respondents' judgment on the relevant factors that affect their online shopping in this pandemic. All items are described by the 0-1 dichotomy method.

In order to make it easier to fill in the questionnaire, the questionnaire was first uploaded to the Star Questionnaire platform. By adding the setting that the same device and the same IP address could only fill in once, the repeated answers of respondents were further excluded to avoid data duplication. Finally a valid link () was obtained. A combination of targeted and non-targeted methods was used to promote the questionnaire links. After a week of data collection, a total of 517 questionnaires were finally obtained. The corresponding evaluation index system is presented in Table A1.

2.4 Data processing

First, all the collected questionnaires were preprocessed by the following rules: the time for completing the questionnaire and the consistency of item selections. This study believes that if the time for completing a questionnaire is too long or too short, and the scores of most items in the same questionnaire are highly consistent (more than 80% of the items have the same score), then the questionnaire is likely to be unreasonable to some extent. In addition, 27 respondents were under the age of 18, accounting for 5.22% of the total. On the one hand, adults are more mature in minds, so the analysis of the key factors behind adults' choice of online shopping has certain universality for further guiding online vendors to better serve the public in the pandemic, and for the government crisis management. In addition, adults over the age of 18 were the main force of online shopping. Based on this, in the subsequent empirical analysis, 27 survey questionnaires from respondents under the age of 18 were excluded. Finally, a total of 456 valid samples were obtained after excluding 61 invalid questionnaires.

3. Empirical Result and Discussion

3.1 Descriptive analysis

Before the empirical analysis, a descriptive statistical analysis is conducted on the obtained samples. First, the completion rate of the sample items is 100%; second, through the analysis of individual samples, no obvious systematic deviation has been found. Therefore, this data collection is reliable, and the descriptive statistical analysis results are given in Table 1.

Table 1. **Descriptive statistics**

Variable	Categorical variable	Proportion (%)
Y= Will you shop online during the pandemic?	1-Yes	77.24
	0-No	22.76
X_1=Gender	1-Male	41.34
	0-Female	58.66
X_2=Age	1-Over 18 years old	94.78
	0-Under the age of 18	5.22
X_3=Educational level	1-College degree or above	81.84
	0- Below college degree	18.16
X_4=Will the no-contact service provided during the pandemic contribute to your selection of online shopping?	1-Yes	81.22
	0-No	18.78
X_5= Will the increase in commodity prices (such as masks) impact your purchase of this product during the pandemic?	1-Yes	47.81
	0-No	52.19
X_6= Will the poor service attitudes of online suppliers affect your purchase of their products during the pandemic?	1-Yes	58.25
	0-No	41.75
X_7= Will the opinions of people around you during the pandemic affect your online shopping?	1-Yes	77.81
	0-No	22.19
X_8= Will the shutdown of offline shopping channels during the pandemic prompt you to switch to online shopping?	1-Yes	85.3
	0-No	14.7
X_9= Will the shortage of products such as disinfectant in the pandemic affect your online shopping?	1-Yes	32.71
	0-No	67.22
X_{10}= Given the possible logistics delays during the pandemic, will you still choose online shopping?	1-Yes	79.54
	0-No	20.46
X_{11}= During the pandemic, will you kill the bored time through online shopping while being stuck at home?	1-Yes	39.46
	0-No	60.54
X_{12}= Will the official information regarding pandemic released during the pandemic further prompt you to choose online shopping?	1-Yes	70.08
	0-No	29.92
X_{13}= During the pandemic, will you stock up goods through online shopping out of panic?	1-Yes	75.37
	0-No	24.63

Source: Author's 2021.

As shown in Table 1, 41.34% of the respondents were males and 58.66% were females. In addition, it can be known from the iResearch (2020) that the top five online shopping categories are household goods, long videos, short videos, online education, and online medical care. These online consumer goods categories further confirm that the gender differences in online shopping are insignificant in this pandemic. Only 5.22% of the respondents were under 18 years old, indicating that the vast majority of the respondents were adults. The respondents with a college degree or above accounted for 81.84%, which indicates that the highly educated have more online purchases than others in this pandemic. Additionally, the consistent of the survey data would be promoted, for the positively participating by the high-educated participators, who would understand the survey more accurately.

3.2 Empirical Findings

This paper used SPSS22.0 statistical analysis software to carry out the corresponding empirical test. First of all, the overall situation of the dependent variable was judged through frequency statistical analysis. Subsequently, through the p value of the standardized coefficient of each respective variable from the Logit regression analysis results, the significance and influence of the independent variable X on the dependent variable Y were analyzed one by one, and the corresponding magnitude of impact was further analyzed in combination with the OR value. At the same time, the Backward:LR method in Logit regression was adopted to further optimize the regression model until all variables in the model had significant effects. Moreover, through the log-likelihood ratio, together with Nagelkerke R^2 and Hosmer-Lemeshow test value, the fitting and validity of each optimization model were comparatively verified. After that, the quality of the optimization models was comparatively judged through the regression prediction accuracy. Finally, the critical factors affecting people's online shopping in this pandemic were summarized. The specific empirical analysis process and results are shown in Table 2-6.

Table 2. **Binary Logit regression analysis results (n=456)**

Dependent variable	Item	Frequency	Percentage (%)
Will you shop online during the pandemic?	0-No	93	20.39%
	1-Yes	363	79.61%
	Total	456	100
Total	Valid	456	100
	Missing	0	0
	Total	456	100

It can be seen from Table 2 that the binary Logit regression analysis is performed with "will you shop online during the pandemic" as the dependent variable in this pandemic. The original assigned values are "yes and no", and the corresponding internal code values are 1 and 0 respectively. Among them, 79.61% of the respondents would choose online shopping, indicating that most people would to make the consumer scene online during the pandemic. A total of 456 valid samples participated in this empirical analysis, and there was no missing data.

Table 3. **The prediction accuracy of the model without independent variables**

Observed result			**Predicted result: Will you shop online during the pandemic? 0**	**1**	**Accuracy**
Initial model	**Will you shop online during the pandemic?**	0	0	162	0%
		1	0	294	100%
	Total (n=456)				64.47%

As shown in Table 3, when the model does not contain any independent variable but only a constant term, its total prediction accuracy is 64.47%. It can be seen from Table 3 that when the corresponding independent variables are included in the model, its prediction accuracy rate rises to 86.84% after seven rounds of model optimization. This shows that the introduction of the corresponding independent variables can significantly improve the prediction effect of the model.

Furthermore, the overall quality analysis of the model. It can be seen from Table 5 that after seven rounds of optimization, the Cox&SnellR^2 and Nagelkerke R^2 in model 7 are 0.493 and 0.541 respectively, which are significantly improved compared with 0.302 and 0.355 in model 1. This demonstrates that after multiple rounds of optimization, the overall goodness of fit of the model is further enhanced. According to the Hosmer-Lemeshow test value, the p value in model 7 is 0.530>0.05, indicating that model 7 has passed the HL test and has a high goodness of fit. It can be seen from the likelihood-ratio test that although the P values of model 1 and model 7 are both below 0.05, after several rounds of optimization, the AIC and BIC values in model 7 are greatly lower than those in model 1. This further proves that the overall effectiveness of model 7 is better than model 1. The index values in the model quality analysis shows that the overall quality of the optimized model 7 is better, which provides necessary support for the subsequent empirical analysis.

Table 5. **Empirical analysis results (n=456)**

Independent variable	Model 1					Model 7				
	β	S.E.	Z	P	OR	β	S.E.	Z	P	OR
X_1	-0.003	0.240	-0.011	0.991	-0.003					
X_3	-0.124	0.314	-0.397	0.691	-0.124					
X_4	1.046	0.385	0.417	0.001	0.985	1.002	0.298	0.578	0.000	2.801
X_5	0.117	0.254	0.459	0.646	1.124					
X_6	-0.301	0.251	-1.199	0.231	0.740					
X_7	0.651	0.313	2.082	0.037	0.521	0.416	0.247	1.682	0.039	0.660
X_8	0.754	0.321	1.322	0.015	0.889	0.823	0.304	1.002	0.009	1.306
X_9	-0.095	0.297	-0.320	0.749	0.909					
X_{10}	1.023	0.262	3.912	0.000	2.782	1.051	0.253	4.145	0.000	2.86
X_{11}	0.196	0.270	0.728	0.467	1.217					
X_{12}	0.925	0.301	3.075	0.002	2.522	1.065	0.281	3.786	0.000	2.899
X_{13}	0.338	0.349	0.969	0.332	1.403	0.643	0.318	2.024	0.043	1.902
Constant β_0	0.579	0.656	0.882	0.378	0.579	0.162	0.231	0.699	0.485	1.176
Cox&SnellR^2	0.302					0.493				
Nagelkerke R^2	0.355					0.541				
Hosmer-Lemeshow test	χ^2=4.65 (P=0.794; df=8)					χ^2=5.107(P=0.53; df=7)				
Likelihood-ratio test	χ^2=51.11 (P=0.000; df=13)					χ^2=46.394(P=0.000; df=6)				
AIC	486.678					463.395				
BIC	544.994					494.222				

Notes: Cox&SnellR^2 and Nagelkerke R^2 test the overall goodness of fit of the model. The value ranges from 0 to 1, and the closer it is to 1, the higher the goodness of fit of the model, and vice versa. The Hosmer-Lemeshow test is to verify the goodness of fit of the model from another aspect. If p>0.05, then HL passes the test; otherwise, it does not. The likelihood-ratio test is used to analyze the validity of the overall model. If P<0.05, the model is valid; otherwise it is not. AIC and BIC are used for comparative analysis in the multi-round optimization of the model, and the lower the two values, the better.

Analysis of insignificant variables in the model. It can be seen from Table 5 that after 7 rounds of optimization, 6 variables including X_1 in the model are excluded. Specifically, the regression coefficient of gender (X_1) is -0.003, but the statistics are insignificant (z=-0.011, p=0.991>0.05). This indicates that gender was not a key factor affecting online shopping in this pandemic, which is different from the situation in which online shopping is dominated by women under normal background. The regression coefficient of educational level (X_3) is -0.124, but it is insignificant (z=-0.397, p=0.691>0.05). This means that educational level was not a major factor influencing consumers' online shopping in this pandemic, which is different from the significant impact of educational level on online shopping under normal background. The regression coefficient of commodity price increase (X_5) is 0.117, but it is not statistically significant (z=0.459, p=0.646>0.05). This demonstrates that due to the impact of COVID-19 pandemic, the consumers were not sensitive to commodity price. This result is also different from the fact that commodity price increase has a significant impact on consumers' online shopping behavior under normal background. The regression coefficient of the poor service attitude (X_6) of the online suppliers is -0.301, but it is statistically insignificant (z=0.-1.199, p=0.231>0.05). This shows that the service quality perception of online shopping during the pandemic did not have a significant effect on the shopping intension of the general public, which is contrary to the conclusion that the perception of service quality significantly impacts consumers' shopping intention under normal background. The regression coefficient of the temporary shortage of products (X_9) in the pandemic is -0.095, yet it is statistically insignificant (z=-0.320, p=0.749>0.05). This means that the shortage of certain products did not affect the online shopping intention/behavior, which is contrary to the conclusion that consumers' purchasing intention/behavior is positively impacted by the scarcity of goods to some extent under normal background. The regression coefficient of relieving the boredom through online shopping while one is stuck at home during the pandemic (X_{11}) is 0.196, but it is insignificant (z=0.728, p=0.467>0.05). This indicates that during this pandemic, the general public did not spend bored time by online shopping. There were two possible reasons: the outbreak of the COVID-19 pandemic was around the Spring Festival of China when the expressage was generally shut down; even if the pandemic had prevented people from visiting relatives and friends during the Spring Festival, the sudden outbreak and the festive atmosphere distracted the masses from the boredom arose from being stuck at home.

3.3 Major factors affecting online shopping during the COVID-19 pandemic

Analysis of significant variables in the model. It can be seen from Tables 6 that the regression coefficient of the online shopping's contactless service (X_4) is 1.002, and it is statistically significant at the 1% level (z=0.578, p=0.000<0.05). This shows that the contactless service characteristics of online shopping was one of the key factors affecting the majority's choice of online shopping. Due to the strong infection of the COVID-19, the general public responded to the government's call to fight against the pandemic by staying at home. In this case, online shopping became quite popular because its non-contact service met the shopping needs of the general public, especially the purchase of daily necessities, but also greatly reduced the contact with the outside world, thus lowering the probability of infection.

Table 6. **Key factors affecting online shopping in the COVID-19 pandemic (n=456)**

	Constant β_0	X_4	X_7	X_8	X_{10}	X_{12}	X_{13}
β	0.162	1.002	0.416	0.823	1.051	1.065	0.643
S.E.	0.231	0.298	0.247	0.304	0.253	0.281	0.318
Z	0.699	0.578	1.682	1.002	4.415	3.786	2.024
P	0.005	0.000	0.039	0.009	0.000	0.000	0.043
OR	1.176	2.801	0.66	1.306	2.860	2.899	1.902

Cox&SnellR^2=0.493; **Nagelkerke R^2**=0.541; **Hosmer-Lemeshow** χ^2=5.107(P=0.530; df=7); **Likelihood ratio** χ^2=46.394(P=0.000; df=6)

The regression coefficient of surrounding people's opinions (X_7) in this pandemic is 0.416, and it is statistically significant at the 10% level (z=1.682, p=0.039<0.05), indicating that the opinions of the surrounding people had a significant impact on online shopping. The rapid spread of the pandemic, the attitudes of the people around towards the pandemic, and the actions they took such as stocking up on food or related anti-pandemic goods might cause the public to follow the herd, which further led to panic buying. Furthermore, the regression coefficient of blocked offline shopping channels (X_8) in this pandemic is 0.823, and it is statistically significant at the 5% level (z=1.002, p=0.009<0.05). This shows that the shutdown of offline shopping channels during the pandemic was one of the key factors that contributed to online consumption. Because many offline stores closed their doors to fight the pandemic, which further encouraged the general public to make the consumer scene online.

Moreover, the regression coefficient of logistics inefficiency (X_{10}) in this pandemic is 1.051, which is significant at the 1% level (z=4.415, p=0.000<0.05). This means that the low efficiency of logistics during the pandemic had a significant positive impact on online shopping, and this conclusion is contrary to the situation that online shopping is negatively affected by low-efficiency logistics under normal background. In the follow-up survey, it was found that the general public understood the situation that the logistics efficiency was greatly reduced due to the lockdown of cities and blockage of roads throughout the country during the pandemic. At the same time, they respected the logistic staff for overcoming every difficulty to deliver packages in this particular period. In addition, in the eyes of the general public, the low efficiency of logistics was an external reflection of the severe pandemic, which therefore did not prevent them from online shopping, but became a key contributing factor of online shopping. In addition, the regression coefficient of the official pandemic information (X_{12}) is 1.065, which is significant at the 1% level (z=3.786, p=0.000<0.05), indicating that official information related to the pandemic had a significant positive impact on online shopping. The Chinese government released timely information related to the pandemic to the general public with full transparency and responsibility, so that they could get the latest developments of the pandemic in the first place. In the early and middle stages of the pandemic in particular, the rapid spread and delayed turning point of the pandemic not only increased the tension of the masses, but also partly stimulated them to make more online purchases.

Finally, the regression coefficient of online shopping out of panic (X_{13}) in the pandemic is 0.643, which is significant at the 10% level (z=2.024, p=0.043<0.05). It shows that the public panic in this pandemic had a certain effect on their online shopping. The sudden outbreak of COVID-19 pandemic was easy to cause social panic among the masses. The research results show that public panic is only significant at the 10% level. Compared with other factors significant at the 5% or 1% level, public panic has a certain impact, but the impact is not significant. This means that the pandemic raised a certain panic among the public, but it was not serious.

4. Conclusion

This study was carried out during the national fight against the COVID-19 pandemic, aiming to investigate the key factors affecting online shopping during this period. In this paper, a mathematical statistical model of influencing factors of online shopping was constructed based on relevant literature and experts' suggestions, and a corresponding questionnaire was developed for data collection. According to the empirical results, the model has good fitting and validity, and after optimization, its prediction accuracy increased from 64.47% at the beginning to 86.84%, indicating that the model construction was appropriate and satisfactory. After 7 rounds of model optimization, it was found that the major factors affecting online shopping in this pandemic are quite different from those under normal background. Specifically, those key factors, such as consumer's gender (X_1), educational level (X_3), commodity prices (X_5), online business service attitudes (X_6), product shortages (X_9), and blind shopping caused by boredom (X_{11}), that have been confirmed by most studies to have a significant effect on online shopping in normal conditions failed the significance test in this study. By contrast, the contactless service characteristics of online shopping (X_4), the opinions of people around about the pandemic situation (X_7), the shutdown of offline shopping channels (X_8), low-efficiency logistics (X_{10}), official pandemic information (X_{12}), and the panic arose from the pandemic (X_{13}) were the major factors influencing the online shopping of the general public in this pandemic.

From the analysis of influencing factors, it was found that the key factors affecting online shopping of the general public during the pandemic differ significantly from those under normal background. For example, the key factors like gender and educational level that have been widely proven to have a significant effect on online shopping under normal background are not significant under abnormal background. Furthermore, the contactless service characteristics of online shopping, the factor has insignificant impact on online shopping under abnormal background, became a major influencing factor of online shopping due to the impact of the pandemic. It should be pointed out that with the gradual improvement of the situation, the influences of these factors would dwindle, and the key factors that affect online shopping under normal background would exert their due effects and dominate again. Among all the critical influencing factors, the contactless service characteristics of online shopping (X_4) and the shutdown of offline shopping channels (X_8) are the unique features of this pandemic. The impact of these two characteristics appeared to weaken as the pandemic situation became better. Nevertheless, the convenience and other experiences brought by online shopping may further influence the general public's choice of online shopping even after the pandemic subsided. Hence, while taking advantages of the benefits brought by the pandemic to the industry, e-commerce companies should pay more attention to fostering customer loyalty after the pandemic.

1. Implication of the Study

While staying at home for fighting against the pandemic, the general public communicated and shared information with others via social software like QQ and WeChat. In the middle and early stages of the outbreak in particular, the development trend of the pandemic was not clear. During this period, the information related to the pandemic from the people around could easily cause a negative impact on the public's mood, which further resulted in panic buying. Thus, on the one hand, the government needs to adopt more effective means to stop the pandemic so as to give hope and confidence to the general public. On the other hand, the government should enhance the positive guidance from public opinion and other aspects, so that the vast majority can become positive energy transmitters, thereby reducing the probability of panic buying and maintaining the stability of social order.

In order to effectively prevent the pandemic, after Hubei (Wuhan), where the situation was the most severe, took the lead in lockdown measures, other provinces across China followed up by taking actions such as blocking roads and setting up COVID-19 symptom detection stations. In addition to reducing the logistics efficiency, these measures further exacerbated the severity of the pandemic in the eyes of the public. As a result, the low efficiency of logistics and delivery during the pandemic became a key contributing factor of online shopping instead. Therefore, relevant government departments should try to ensure the normal operation of logistics related closely to the production and daily necessities while shutting down the city to prevent the pandemic. This is conducive to the effective circulation of the production and living supplies, and meanwhile it can better meet the purchasing needs of the public while fighting the pandemic at home, which helps to alleviate their negative emotions and better consolidate the achievements in fighting the pandemic.

In the COVID-19 pandemic, the Chinese government used the Internet and big data and other emerging technologies to release the pandemic-related information to the public timely and objectively. Especially in the middle and early stages of the pandemic, the information about the increasingly severe pandemic not only revealed the truth to the public but also shock them, which partly exacerbated the severity of the pandemic in the eyes of the general public, thereby causing them to stockpile goods. Therefore, while sharing the development of the pandemic timely and transparently with the whole society, the government must also appease the possible social panic arising from the pandemic, for example by sharing the positive events emerged during the pandemic, announcing the latest achievements of scientific research on COVID-19, providing psychological counseling services, etc. In this way, it is not only conducive to establishing a good government image, but also guaranteeing the general public's right to see the full picture of the pandemic, thereby maintaining social stability.

2. Limitations and Directions for Future Study

There are a few drawbacks to our analysis. First, self-reporting has shortcomings compared to personal interviews with various assumptions. Sample errors that can influence the public to estimate major factors relating to online shopping during this pandemic often comprise distortions. Secondly, because this study was an online survey, it does not represent everyone outside the internet. Third, this is a cross-sectional analysis that only describes the factors affecting online shopping based on the opinions of respondents, not their influence at varying periods. Longitudinal observation is crucial, particularly if there is a possible post-traumatic experience. Fourth, the study utilized a logistic regression model using SPSS, which may be extended in the future studies by employing the Partial Least Square-Structural Equation Modeling or covariance-based Structural Equation Modeling approach to structural equation modeling. Therefore, future research will provide more descriptions of COVID-19's interpretation of the variables studied. Future experiments can also use an experimental framework to detect accurate outcomes.

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Conflicts of Interest

The authors declare no conflict of interest.

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Appendices

Table A1. **Key influencing factors of online shopping in the COVID-19 pandemic**

Variable	Definition of variable	Value range
Y	Will you shop online during the pandemic?	1=Yes; 0=No
X_1	Gender	1=Male; 0=Female
X_2	Age	1=Under 18 years; 0=Over 18 years
X_3	Educational level	1=below college; 0=above college
X_4	Will the no-contact service provided during the pandemic contribute to your selection of online shopping?	1=Yes; 0=No
X_5	Will the increase in commodity prices (such as masks) impact your purchase of this product during the pandemic?	1=Yes; 0=No
X_6	Will the poor service attitudes of online suppliers affect your purchase of their products during the pandemic?	1=Yes; 0=No
X_7	Will the opinions of people around you during the pandemic affect your online shopping?	1=Yes; 0=No
X_8	Will the shutdown of offline shopping channels during the pandemic prompt you to switch to online shopping?	1=Yes; 0=No
X_9	Will the shortage of products such as disinfectant in the pandemic affect your online shopping?	1=Yes; 0=No
X_{10}	Given the possible logistics delays during the pandemic, will you still choose online shopping?	1=Yes; 0=No
X_{11}	During the pandemic, will you kill the bored time through online shopping while being stuck at home?	1=Yes; 0=No
X_{12}	Will the official information regarding pandemic released during the pandemic further prompt you to choose online shopping?	1=Yes; 0=No
X_{13}	During the pandemic, will you stock up goods through online shopping out of panic?	1=Yes; 0=No

Table A2. **Prediction accuracy of the model (n=456)**

			Predicted value		Prediction accuracy	Prediction error rate
			0	1		
Model 1	**Actual value**	0	63	45	58.33%	41.67%
		1	56	292	83.91%	16.09%
		Total			77.85%	22.15%
			Predicted value		**Prediction accuracy**	**Prediction error rate**
			0	1		
Model 7	**Actual value**	0	78	30	72.22%	27.78%
		1	30	318	91.38%	8.62%
		Total			86.84%	13.16%