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Review Article

Effect of New Media Communication on Consumer Behavior Based on Industrial Edge Cloud Deployment Algorithm

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In the era of advanced information technology, new media represented by mobile phones have the characteristics of fast information dissemination, unlimited time, and place, and they are loved by people. Just like this, many businesses and enterprises use new media tools to promote and sell product information, and they have achieved positive results. In this context, this paper mainly studies the impact of new media communication on consumer behavior. By combining the characteristics of the industrial edge cloud deployment algorithm, an analysis model of behavior influencing factors is constructed, and relevant analysis is carried out. This paper mainly obtains experimental data by means of questionnaires and conducts experimental demonstrations for the proposed hypotheses. Before the experiment, the algorithm is compared and analyzed, and it is concluded that when the production line is 50, the algorithm in this paper is 0.6% and 0.32% lower than other algorithms under the SER index. When the production line is 100, the algorithm in this paper is 9.9% and 6.3% lower than other algorithms under the ELDR index. When the production line is 150, the algorithm in this paper is 2.2% and 2.4% lower than other algorithms under the ACR index, indicating that the performance of the algorithm in this paper is better than other algorithms under the SER, ELDR, and ACR indexes. In the correlation and regression analysis of variables, the results show that there is a positive relationship between consumer behavior and consumer willingness. At the same time, there is a positive relationship between consumer willingness and perceived novelty, perceived value, perceived interactivity, and perceived usefulness of new media. The coefficients of its functional expression are 0.411, 0.378, 0.241, and 0.216, respectively, verifying the assumptions 3, 5, 7, and 8 hold. It shows that consumer behavior is affected by consumer willingness, and consumer willingness is most affected by the perceived novelty of new media, followed by new media perceived value, perceived interactivity, and perceived usefulness.

1. Introduction

In this period of information data explosion, a large amount of media information is flooding around us. The external information we receive is not limited to the past paper newspapers and news broadcasts. The development of information technology has brought us great convenience, and we can obtain the information we want anytime, anywhere. Especially with the rapid development of Internet technology and technology, new media tools such as mobile phones and the Internet of Things are deeply loved by people. With the development of technology, more and more new media communication tools are recognized by people. In the past period of time, people wanted to obtain product information only by on-site verification or through other consumers to understand and so on. The key information of the product obtained in this way is limited, and a lot of time is wasted. In this context, the change of new media has brought a huge impact on this phenomenon. New media communication has the characteristics of real-time and social. It can be said that the new media has brought great help to people's lives, especially in the commercial field. Enterprises from all walks of life have used new media to provide services such as information dissemination and product promotion and have achieved many good results. For consumers, consumers can use the mobile phone as a new media tool to learn about product information, and even communicate with other consumers to truly understand the true value of familiar products. Therefore, this paper mainly selects the latitude of the impact of new media communication on consumer behavior as a research entry point to find out the factors that affect consumer behavior.

Today's way of information dissemination breaks the channels of the past that could only be disseminated through print newspapers or news broadcasts. What follows is a new mode of new media communication. Under this circumstance, consumers' consumption concept and consumption behavior will also change accordingly. In terms of product and service information, consumers can quickly understand the product information and even have a multi-angle understanding of the product through video playback. Not only that, consumers can interact with other consumers, understand the advantages and disadvantages of products, and then judge whether the product meets their expectations, etc., which further deepens consumers' dependence on new media. Especially in the current online shopping, most consumers will refer to the information spread by new media and then make consumption behaviors. For the current consumer group, there is a connection and influence between consumption willingness and consumption behavior and new media communication. This question provides some ideas for the research of this paper. Its research content not only enriches the theoretical research of consumer behavior but also provides certain practical guiding significance for the marketing plan of enterprises.

With the technological innovation of new media, more and more people like to consume through new media. Not only consumers but many companies also disseminate product information through new media so as to achieve the behavior of consumers purchasing company products. Many scholars have carried out research on this. Gupta S studied the relationship between CSR-S on brand adoration and consumer purchase intention. Taking consumers in the banking industry as the research object, he used the AMOS structural equation to analyze the data and concluded that CSR-S was positively correlated with purchase intention, and the result was also recognized by the bank [1]. Baum D aimed to study that social media platforms can promote the dissemination of new products in society and expand their reach, and extensively analyzed the impact of online word-of-mouth communication and social interaction on consumer behavior [2]. Anshari et al. used millennials as the research object to analyze the behavioral characteristics of consumers. Studies have found that millennials are dependent on social media, and using social media as a shopping platform, they are more willing to try new things [3]. Yichuan and Chiahui used WOM to communicate and observe other consumers' buying behavior. He studied their impact on consumer purchase intentions and actual purchase behavior. By analyzing the relevant data before and after purchase, it is concluded that positive and negative WOM, WOM content, and observing other consumers' purchase behavior will significantly affect consumers' purchase intention, thereby increasing the possibility of actual purchase and sharing product information with others [4]. Zangnaa et al. analyzed the behavior of customers to purchase products when exposed to online advertisements. The results show that factors such as service, product convenience, and cost are positively correlated with the actual purchase behavior of customers when exposed to online advertisements [5]. It can be seen that most consumers are willing to contact new media and believe in the dissemination of information by new media. When analyzing the impact of new media communication on consumer behavior, the data is complicated because of the many factors that affect new media communication. The degree of influence of different factors is not necessarily the same, and ordinary methods can no longer meet the needs. Therefore, it is necessary to seek new methods to analyze the influence degree of factors. This article mainly analyzes the influence degree with the help of the industrial edge cloud deployment algorithm. Wang J found that edge cloud computing can solve the shortcomings of the only centralized cloud computing model. He moved computing and storage resources closer to the device to support multimedia transmission, artificial intelligence, and other applications [6]. Nguyen et al. analyzed the effective placement and chaining of VNFS through edge cloud deployment to provide cloud-based IoT services with minimal resource usage costs [7]. Zhang et al. found that edge cloud can not only improve the performance of computing services but also support a huge amount of computing, effectively improving the utilization of data resources [8]. To sum up, the deployment of industrial edge cloud can calculate and analyze the data of influencing factors of new media propagation, which can effectively improve the utilization rate of data.

On the basis of referring to previous related research, this paper analyzes the impact of new media communication on consumer behavior with the help of industrial edge cloud deployment algorithms and conducts in-depth data analysis on the shallow-level research in the past. A new model is constructed through the industrial edge cloud deployment algorithm, and the impact of indicators such as consumer willingness, new media novelty, new media ease of use, and usefulness on consumer behavior is studied and analyzed. Through the new model to explore the correlation between consumer behavior and influencing factors, the functional relationship expression of consumer behavior is finally obtained. The coefficient of its independent variable indicates its influencing factors and degree of influence. At the same time, the model constructed based on the industrial edge cloud deployment algorithm is innovative to a certain extent, and the results also have certain guiding suggestions.

2. Theories Related to Industrial Edge Cloud Deployment and New Media Dissemination

2.1. New Media Communication. In today's trend, "new media" is mainly based on digital technology and disseminates information through Internet media, and with the advancement of science and technology, new media will become more and more [9]. This paper mainly defines new media as digital media, WeChat, Weibo, and other new digital media [10]. In order to better explain the impact of new media communication on consumer behavior, this paper focuses on analyzing the characteristics of new media communication:

2.1.1. The National Character of New Media Communication. Compared with the traditional media in the past, the current new media communication can carry out two-way communication, and everyone can express and comment on an event through the new media [11]. Everyone can be both a disseminator and a receiver of information. This allows information to be sourced more widely, spread faster, and truly realize the phenomenon that everyone is a media person. This situation has a profound impact on consumers' online shopping behavior, changing the past habit of passively receiving information.

2.1.2. Diversification of New Media Communication. Compared with traditional media communication, new media communication allows consumers to have a comprehensive understanding of information. Consumers can recognize products not only through a few paragraphs of text but also through pictures or even videos, which perfectly explains product information [12]. Not only that, new media technology allows each consumer to have an exclusive private account. This account only represents the relevant information of the consumer, such as consumers focus on consumer information such as product brand, product price, or shopping preferences, and the information pusher can send these specific information to the consumer's private account according to their own marketing needs. To achieve the purpose of pushing effective information to consumers, consumers can also conduct specific searches according to their own needs to choose information that suits their appetite.

2.1.3. The Speed of New Media Spread. With the improvement of technology, the speed of information dissemination in new media is extremely fast. It can be said that information can be delivered to consumers in just a few seconds, and consumers can also quickly understand product information through the retrieval function. The dissemination of information is not limited by time and place and can even be shared through Bluetooth. It can be said that as long as people want, people can get the information they want at anytime and anywhere.

2.2. Theory of Industrial Edge Cloud Deployment Algorithms. The industrial edge cloud is the key to building the edge digital twin technology architecture and providing real-time operation and maintenance services [13]. Because the resources of the industrial edge cloud are limited, when the size of the factory changes, the limited resources must be properly deployed. Reasonable industrial edge cloud deployment not only reduces company costs and industrial edge cloud load but also improves service quality [14]. A schematic diagram of an industrial edge cloud deployment is shown in Figure 1.

Suppose $\mathrm{AC} = \left\{\mathrm{AC}_1, \mathrm{AC}_2, \ldots, \mathrm{AC}_{|m|}\right\}$ is a set of edge clouds, where $|m|$ is the total number of edge clouds, $\mathrm{T} = \left\{\mathrm{T}_1, \mathrm{T}_2, \ldots, \mathrm{T}_{|n|}\right\}$ is a set of production lines, and $|n|$ is the total number of production lines. For any i, the production line $\mathrm{T}_i = \left\{\mathrm{AQ}_1^i, \mathrm{AQ}_2^i, \ldots, \mathrm{AQ}_{|\mathrm{AQ}^i|}^i\right\}$ consists of a set of production equipment AQ_j^i. Among them, $j \in [1, \mathrm{AQ}^i]$ and $|\mathrm{AQ}^i|$ are the total number of production equipment of the production line T_i. When there is a set of edge cloud sets, under the constraint condition $\mathrm{Cost}[\mathrm{AC}]$, the value of $\mathrm{Delay}[\mathrm{AC}], \mathrm{Balance}[\mathrm{AC}]$ is minimized, and the expression of the objective function is as follows:

$$\begin{aligned} &\mathrm{minDelay}[\mathrm{AC}](\mathrm{X}) \&\& \mathit{minBalance}[\mathrm{AC}](\mathrm{X}) \\ &\qquad \mathrm{Const}[\mathrm{AC}](\mathrm{X}) \le \mathrm{Const}_c, \end{aligned} \tag{1}$$

where X is the deployment plan and Const_c is the cost control amount of the enterprise.

The summation formula of total edge cloud services is as follows:

$$\mathrm{Delay}[\mathrm{AC}] = \sum_{i=1}^{|\mathrm{AC}|} \mathrm{Delay}[\mathrm{AC}_i]. \tag{2}$$

When there is a service delay for each production line, the relational expression between AC_i and production line is as follows:

$$\begin{aligned} \mathrm{Delay}[\mathrm{AC}_i] = &\sum_{i}^{|\mathrm{T}|} \sum_{j}^{|\mathrm{AQ}^i|} \mathrm{Y}\left[\mathrm{AC}_i, \mathrm{AQ}_j^i\right] \\ &+ \sum_{i}^{|\mathrm{T}|} \mathrm{Dispose}[\mathrm{AC}_i, \mathrm{T}_i], \end{aligned} \tag{3}$$

where Y is the data transmission delay between the production device and the edge cloud, and Dispose is the processing delay of the edge cloud service.

The summation formula of the total load of the edge cloud is as follows:

$$\mathrm{Balance}[\mathrm{AC}] = \sum_{i=1}^{|\mathrm{AC}|} \mathrm{Balance}[\mathrm{AC}_i]. \tag{4}$$

A single edge cloud AC_i load includes memory consumption, CPU consumption, etc. The calculation formula is as follows:

$$\begin{aligned} \mathrm{Balance}\left[\mathrm{AC}_i\right] = &\sum_{j}^{|\mathrm{T}|} \mathrm{BCPU}\left[\mathrm{AC}_i, \mathrm{T}_j\right] \\ &+ \sum_{j}^{|\mathrm{T}|} \mathrm{BCACHE}\left[\mathrm{AC}_i, \mathrm{T}_j\right] \\ &+ \sum_{j}^{|\mathrm{T}|} \sum_{k}^{|\mathrm{AQ}^j|} \mathrm{BCOM}\left[\mathrm{AC}_i, \mathrm{AQ}_k^j\right], \end{aligned} \tag{5}$$

where BCPU is the CPU consumption, BCACHE is the memory consumption, and BCOM is the communication consumption.

Industrial edge cloud deployment generally deals with constrained multi-objective optimization problems, but in practice, there are problems such as multiple coverage, which

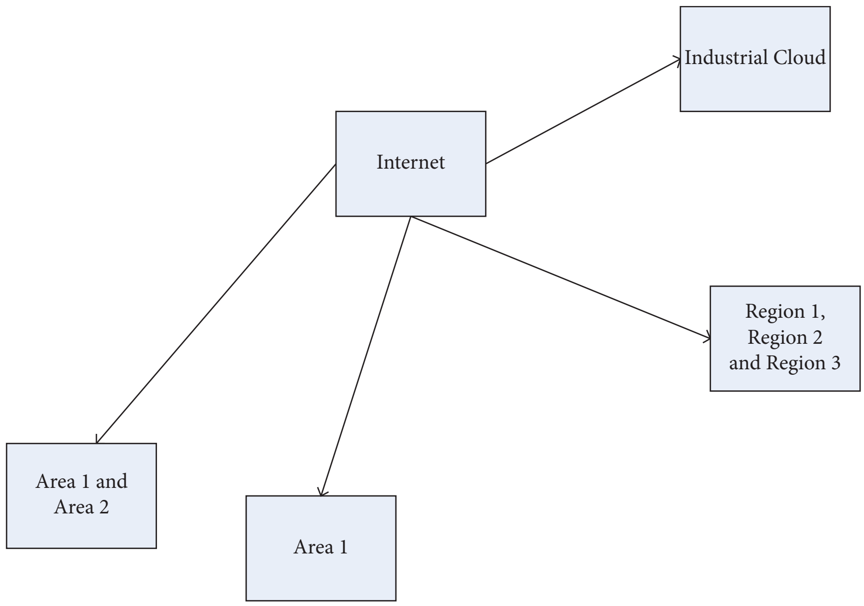

Figure 1: Industrial edge cloud deployment diagram.

make the calculation process extremely cumbersome [15]. Therefore, it is necessary to perform dimensionality reduction processing, thereby reducing the calculation process. We divide the weight of the objective function in the above calculation process [16]. Its specific operation formulas are as follows:

$$
\begin{aligned}
&\min\left\{\sum_{T_a}\sum_{T_j\in T_a}\text{Weight}_j\right\},\\
\% \quad &\sum_{T_a}\sum_{T_j\in T_a}\text{Const}_{T_j}\le \text{Const}_c,\\
&T_a=\varnothing\cap,\\
&\cup T_a=T.
\end{aligned}
\tag{6}
$$

When we deploy the industrial edge cloud, we must not only consider the configuration problem of maximizing the benefit of limited resources but also keep the load in a balanced state. Only reasonable scheduling can achieve benefit maximization and load balancing problems [17]. Its formulas are as follows:

$$
\begin{aligned}
&T=TC+TR\\
\% \quad &TC=\begin{bmatrix} tc_{11} & \ldots & tc_{1m}\\ \ldots & \ldots & \ldots\\ tc_{n1} & \ldots & tc_{nm}\end{bmatrix},\\
&tc_{ij}=\frac{Q_i}{C_j},
\end{aligned}
\tag{7}
$$

where TC is the computation delay matrix, TR is the transmission delay matrix, tc_{ij} is the computation delay of device *i* on edge server *j*, and Q_i is the maximum load of device *i*. C_j is the computing capability of edge server *j*.

When the task is transmitted, there may be multiple accesses, and the transmission delay during the transmission process needs to be considered [18]. Its calculation formulas are as follows:

$$
\begin{aligned}
&TR=\begin{bmatrix} tr_{11} & \ldots & tr_{1m}\\ \ldots & \ldots & \ldots\\ tr_{n1} & \ldots & tr_{nm}\end{bmatrix},\\
&N_{ij}=\frac{d(i,j)}{d_{ave}},\\
&tr_{ij}=N_{ij}\times\frac{D_i}{B},
\end{aligned}
\tag{8}
$$

where tr_{ij} is the transmission time, $d(i,j)$ is the transmission distance, d_{ave} is the distance per visit, N_{ij} is the number of visits per visit, B is the network bandwidth, and D_i is the load data volume of device *i*.

The expression of the load data volume of edge server *j* is as follows:

$$
cl_j=\sum_{i=1}^{n}x_{ij}\times Q_i,
\tag{9}
$$

where x_{ij} is a binary variable. When $x_{ij}=1$, there is an association between *i* and *j*; when $x_{ij}=0$, there is no association between *i* and *j*.

The data processing delay calculation formula for edge computing is as follows:

$$
MT=\max\sum_{i=1,1\le j\le m}^{n}\left(x_{ij}\times T_{ij}\right).
\tag{10}
$$

The load balancing expression for edge computing is as follows:

$$LB = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(\frac{cl_j}{c_j} - \frac{1}{m}\sum_{j=1}^{m}\frac{cl_j}{c_j}\right)^2}. \tag{11}$$

When the value of LB is smaller, the computing load of the edge server is closer to a balanced state.

3. Model Construction and Design Based on Industrial Edge Cloud Deployment Algorithm

When we analyze the impact of new media communication on consumer behavior, we need to build a corresponding model for data analysis. In order to accurately understand the nature of the impact of new media communication on consumer behavior, we rely on the principles of qualitative and quantitative and multi-factor analysis. Combining the characteristics of industrial edge cloud deployment algorithms, such as automatic and intelligent processing of massive data, real-time processing of data and distributed, etc., an information technology acceptance-consumer behavior model is constructed to analyze the impact of new media communication on consumer behavior [19]. Its theoretical model is shown in Figure 2.

3.1. Comparative Deconstruction of Algorithms. In order to verify the advantages of the industrial edge cloud deployment algorithm, this paper selects the ESP, the ACPM algorithm, and the industrial edge cloud deployment algorithm to compare and analyze the ELDR, ACR, and SER indicators. The smaller the value, the better [20]. When the total deployment cost is constant, the above algorithm is tested by increasing or decreasing the production line. The analysis results are shown in Figures 3–5.

3.1.1. Comparison of SER Indicators. It can be seen from Figure 3 that with the increase of production lines, the SER under different algorithms also shows an increasing trend. When the number of production lines is 50, the values of ESP, ACPM, and IECDA are 1.4%, 1.12%, and 0.8%, respectively, of which IECDA is 0.6% and 0.32% lower than other algorithms. It shows that the IECDA algorithm is superior to other algorithms, and the same is true when the number of production lines is 100 and 150.

3.1.2. Comparison of ELDR Indicators. It can be seen from Figure 4 that with the increase of production lines, the ELDRs under different algorithms also show an increasing trend. When the number of production lines is 100, the values of ESP, ACPM, and IECDA are 18.2%, 14.6%, and 8.3%, respectively. Among them, IECDA is 9.9% and 6.3% lower than other algorithms, indicating that the IECDA algorithm is better than other algorithms, and the same is true when the number of production lines is 50 and 150.

3.1.3. ACR Indicator Comparison. It can be seen from Figure 5 that with the increase of production lines, the ACR under different algorithms also shows an increasing trend. When the number of production lines is 150, the values of ESP, ACPM, and IECDA are 7.9%, 8.1%, and 5.7%, respectively. Among them, IECDA is 2.2% and 2.4% lower than other algorithms, indicating that the IECDA algorithm is better than other algorithms, and the same is true when the number of production lines is 50 and 100.

3.2. Hypothesis. In terms of model structure, the model is mainly divided into original variables, intermediate variables, and output variables. Based on relevant theories, this paper puts forward corresponding assumptions for the variables in the model by consulting the relevant literature in the world. Its main assumptions are as follows:

3.2.1. The Influence of Consumer Willingness to Consume on Consumer Behavior. When consumers recognize the value of a product spread by the new media platform, and have a certain willingness to buy this product, it shows that the new media platform can meet the actual needs of consumers. That is, consumers' willingness to consume has a positive impact on their consumption behavior. Therefore, we can put forward the hypothesis: A1—The usefulness of new media has a positive impact on consumers' consumption behavior.

3.2.2. The Impact of Perceived Participation of New Media on Consumer Behavior. The process of users publishing, disseminating, and browsing information on the new media platform can be perceived by the new media platform. These behaviors of users have certain distinctive characteristics. It can be said that consumers can obtain product information through communication, browsing other people's evaluations and other behaviors when they want. Compared with other information channels, consumers are invisibly involved in the dissemination of information on new media platforms, which greatly arouses the enthusiasm of consumers to purchase goods. The higher the participation of consumers, the stronger the willingness of consumers to buy. Therefore, we can put forward the hypothesis: A2—The participation of new media has a positive impact on consumers' consumption behavior.

3.2.3. The Impact of Perceived Interactivity of New Media on Consumer Behavior. The interactivity of new media includes both social and interactive meanings. Simply put, enterprises can share resources, communicate, and interact with consumers through new media platforms. Consumers can truly understand the information and value of commodities through the above methods and avoid the phenomenon of "stepping on thunder." It can be said that the stronger the interactivity of consumers, the deeper consumers' cognition of commodities, and the stronger their willingness to purchase commodities. Therefore, we can put forward the

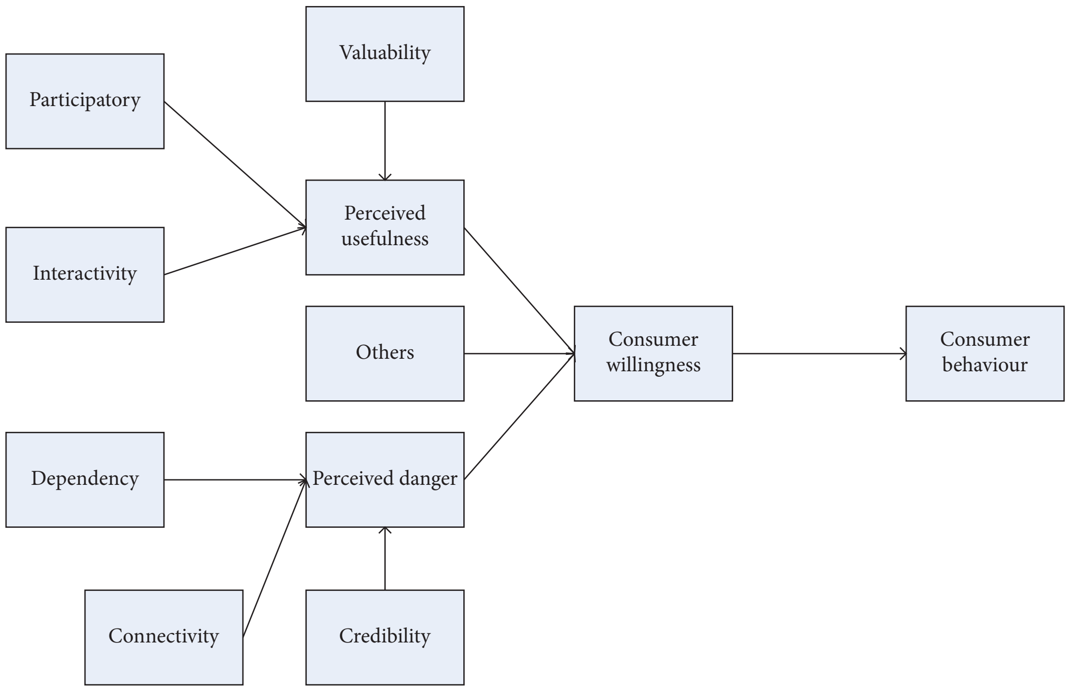

Figure 2: Theoretical diagram of the information technology acceptance-consumer behavior model.

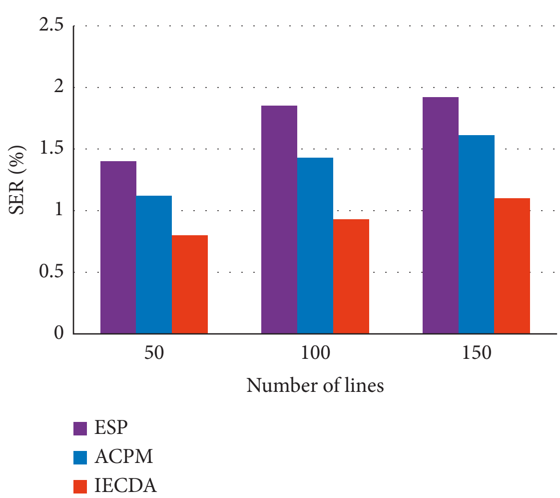

Figure 3: Comparison chart of SER under different algorithms.

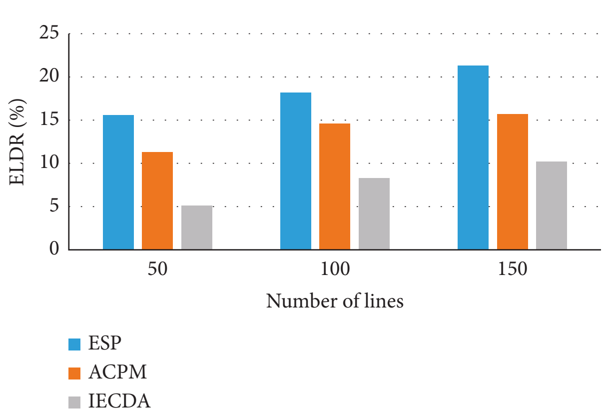

Figure 4: Comparison chart of ELDR with different algorithms.

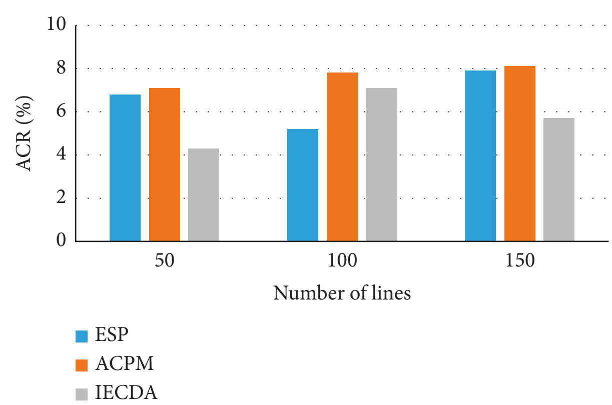

Figure 5: Comparison chart of ACR under different algorithms.

hypothesis: A3—The interactivity of new media has a positive impact on consumers' consumption behavior.

3.2.4. The Impact of Perceived Ease of Use of New Media on Consumer Behavior. The ease of use of new media mainly means that when users use new media software, the lower the difficulty in getting started and the difficulty in operating the software, the better. For example, the current Taobao account is shared with Alipay, and there is no need for additional account registration and bank card binding. While sharing an account, Alipay can be used for consumption payment, which greatly facilitates consumers' consumption behavior. No consumer likes to use complex new media software for shopping, and the simpler the software, the better. When the ease of use of a certain new media software is worse, the less consumers will pay for the software, which greatly reduces consumers' willingness to consume. Therefore, we can put forward the hypothesis: A4—The ease of use of new media has a positive impact on consumers' consumption behavior.

3.2.5. The Impact of Perceived Novelty of New Media on Consumer Behavior. The information release of new media has stronger timeliness than the past media, and users can know the latest product information anytime and anywhere. Not only that, most of the content of new media is original content and rich in content; it can be said to cover all aspects of the current society. Users will have a strong interest in new things or fields, and it is clear that new media can do this. Through the new media platform, new products can be displayed in multiple directions at any time, attracting the attention of consumers. In turn, consumers can learn about the latest developments in the products they need through new media platforms. It can be said that the novelty of new media content will greatly increase the willingness of consumers to consume, thereby triggering consumption behavior. Therefore, we can put forward the hypothesis: A5—The novelty of new media has a positive impact on consumers' consumption behavior.

3.2.6. The Impact of Perceived Risk of New Media on Consumer Behavior. In the daily consumption process, consumers often pursue the principle of maximizing benefits and will not buy non-essential commodities on impulse. When consumers do not know enough about the information of the products or there are unforeseen risks after purchasing unknown products, consumers will make rational choices to avoid the loss of value after shopping. It can be seen that the greater the perceived risk of new media, the less willingness to buy. Therefore, we can put forward the hypothesis: A6—The risk of new media has a negative impact on consumers' consumption behavior.

3.2.7. Consumer Perception of Product Value. When consumers are shopping, they will measure the size between the cost and the benefit they pay and will not buy products whose benefits are far less than their costs. When the value of a commodity is much greater than the cost, consumers will be more willing to buy. It can be said that the value of the commodity affects the behavior of consumers. Therefore, we can put forward the hypothesis: A7—The greater the value of the products released by the new media platform, the positive impact on the behavior of consumers.

3.2.8. Impact of Perceived Usefulness of New Media on Consumer Behavior. Consumers can perceive the use value of new media platforms. The more useful consumers perceive new media, the more willing they will be to use new media, the more they will trust the product information released by the new media platform, and the value of the products released by the new media platform will be recognized. Therefore, we can hypothesize: A8—The usefulness of new media has a positive impact on consumer behavior.

3.3. Variable Deconstruction

3.3.1. Questionnaire Design. The questionnaire designed in this paper is divided into three parts. The first part is the basic information of the respondents, mainly age, gender, monthly consumption amount, etc. The second part is the respondents' cognition of new media, mainly including commonly used new media, inquiring about commodity information, and online communication with other consumers. The third part is the main part of the questionnaire, which mainly evaluates variables such as the usefulness and interactivity of the respondents' perception of new media through the Likert table. In general, respondents need to answer truthfully based on their own circumstances. The Likert scale mainly sets five levels of "strongly agree, agree, moderate, disagree, and strongly disagree" for each question. Corresponding to 1–5, a total of five options are used to measure the degree of agreement of the respondents to the content of the statement.

3.3.2. Sources of Research Variables. The indicators and sources of the questionnaire are shown in Table 1.

3.4. Data Sources. In order to obtain real and effective experimental data, this paper mainly conducts an anonymous questionnaire survey on consumers in Region A by randomly distributing paper questionnaires. A total of 100 questionnaires were distributed this time. After statistical analysis, 92 valid questionnaires were obtained. The effective rate is 92%, which meets the experimental requirements.

4. Experiment of Impact of New Media Communication on Consumer Behavior

4.1. Descriptive Statistical Deconstruction. In order to fully understand the relevant data information of the recovered questionnaires, we need to conduct descriptive statistical analysis on the basic composition and basic situation of the total sample. The analysis results are shown in Figure 6.

Figure 6 is a statistical analysis of the basic information of the surveyed objects. In terms of gender, the ratio of males to females is almost the same, with males accounting for 56.5% and females accounting for 43.5%. In terms of age, it is mainly concentrated in the 18–35 years old, accounting for 72.8%. In terms of marital status, unmarried people are the majority group. In terms of the monthly shopping consumption amount, most people consume between 100 and 1000 yuan, which is a normal consumption level. In terms of online shopping times, 70.7% of the people who shop 3–5 times a month account for the majority. In terms of time spent using new media, the majority of the population was between 30 minutes and an hour.

4.2. Reliability and Validity

4.2.1. Reliability Analysis. In simple terms, reliability analysis is to analyze the stability and reliability of the evaluation system or tool. This paper mainly analyzes the questionnaire

Table 1: Table of model measurement indicators.

Variables	Indicators
Perceived ease-of-use	A1: I think most new media software is easy to use A2: I am skilled in using new media to find product information A3: I am able to use new media quickly
Perceived usefulness	B1: The new media tools I've been exposed to have been helpful B2: New media tools allow me to quickly learn about products B3: The search function of the new media tool is extremely easy and quick B4: Information on products recommended by new media has great value
Perceptual interactivity	C1: New media is consumer-centric, designing interfaces that fit the concept C2: Willingness to spend after interacting with other consumers through new media C3: Willingness to share experiences of using products with others through new media platforms C4: Feedback on products with merchants through new media platforms
Perceptual novelty	D1: If a new media outlet regularly publishes novelty content, I will use it on a regular basis D2: I will follow a merchant if I am interested in the novelty of the information they post D3: I like novelty content
Perceptual participatory	E1: I have free access to new media whenever I want E2: I can interact with other consumers at any time with product information E3: I like to interact with other consumers at all times with product information
Perceived riskiness	F1: I usually trust the product information posted on new media platforms F2: Transactions on shopping platforms are not dangerous enough to make me want to buy F3: Shopping platforms with tight protection measures to protect consumers' money will make me want to shop
Willingness to consume	G1: When a new media platform posts information about an item, I give priority to buying it G2: When I see an item I agree with, I buy it straight away
Consumer behavior	H1: I will make a purchase when I trust the new media to communicate information about the product H2: When I am interested in buying a product on a new media platform, I go through the product information in detail

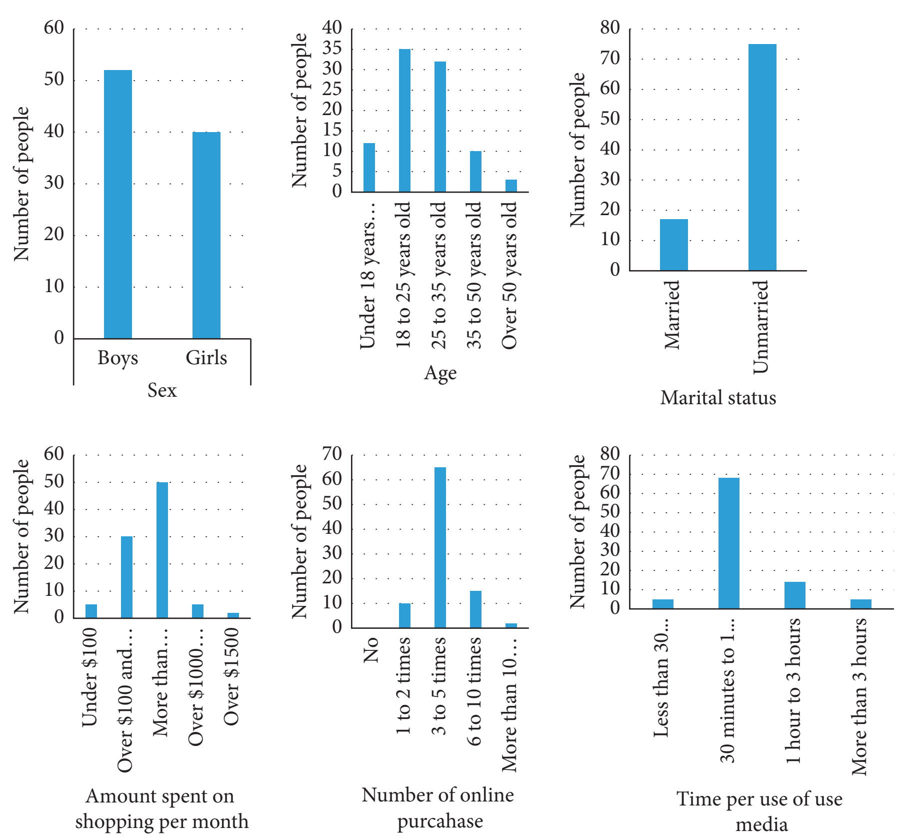

Figure 6: Statistical chart of questionnaire return data.

system, that is, the same measurement group is measured multiple times, and the measurement results should be consistent each time, and the reliability of this measurement tool is considered to be high. In general research, when it is $\alpha < 0.6$, it indicates that the reliability of the scale is insufficient; when it is $0.7 < \alpha < 0.8$, it is considered to have a certain internal consistency; and when it is $\alpha > 0.8$, it indicates that the reliability of the scale is extremely high. According to this method, this paper studies and analyzes the reliability of the questionnaire, and the results are shown in Figure 7.

As can be seen from Figure 7, compared with the lowest reliability coefficient of 0.6, the reliability coefficients of different factors are all greater than 0.6, and the reliability coefficient of the entire questionnaire is 0.789, which belongs to the upper-middle level. It shows that the sample table has good reliability and good internal consistency.

4.2.2. Validity Analysis. Validity analysis is to test whether the questionnaire can accurately reflect the characteristics of the target object and the measurement object. Generally speaking, it mainly analyzes from two aspects: content validity and structure validity. Content validity refers to whether the questions in the questionnaire can comprehensively cover the survey content. Structural validity refers to whether the theoretical structure and characteristics of the questionnaire are reasonable. This paper mainly uses factor analysis to analyze the construct validity, and its test standard is measured by the KMO value and Barlett sphericity. When the value of $0 < \text{KMO} < 1$ is closer to 1, it means that the degree of correlation between the related variables is higher. Generally, factor analysis can be done if the KMO value is greater than 0.6. Barlett's sphericity test for the degree of independence between variables; in general, $p < 0.05$ indicates that it is suitable for factor analysis. Next, KMO, factor analysis, and Bartlett's sphericity test for each variable were performed. When the eigenvalues are all greater than 1, the factor loading is greater than 0.5, and the cumulative variance contribution rate is greater than 50%; it means that the experimental requirements are met. The test results are shown in Table 2.

It can be seen from Table 2 that the validity analysis results of this questionnaire meet the expected requirements. The KMO values, significance probability values, factor-explained cumulative variance contribution rates, factor loadings, and eigenvalues of all its variables meet the standard values. It shows that the data content and structure of the questionnaire are valid, and the data obtained from the analysis are ideal.

4.3. Correlation of Variables

4.3.1. Correlation Analysis between the Characteristics of New Media Communication and Consumers' Willingness. When designing the questionnaire, we divided the factors of new media communication into five dimensions: perceived ease of use, perceived usefulness, perceived interactivity, perceived novelty, perceived participation, and perceived risk. The correlation analysis between the above five dimensions and consumer willingness is carried out to test whether there is a certain correlation between several characteristics of new media communication and consumer willingness. The results are shown in Table 3.

As can be seen from Table 3, the $p = 0.011 < 0.05$ coefficient of the relationship between consumers' perceived ease of use and consumers' willingness is 0.387, indicating that there is a positive and significant correlation. The $p = 0.001 < 0.01$ coefficient of the relationship between consumers' perceived usefulness and consumers' willingness is 0.587, indicating that there is a positive and significant correlation and the correlation is strong. The $p = 0.017 < 0.05$ coefficient of the relationship between consumer perception interactivity and consumer willingness is 0.551, indicating that there is a positive and significant correlation. The $p = 0.046 < 0.05$ coefficient of the relationship between consumers' perceived novelty and consumers' willingness is 0.651, indicating that there is a positive and significant correlation and the correlation is strong. The $p = 0.053 > 0.05$ coefficient of the relationship between consumers' perceived participation and consumers' willingness is 0.213, indicating that there is no positive and significant correlation. The $p = 0.052 > 0.05$ coefficient of the relationship between consumer perceived risk and consumer willingness is −0.183, indicating that there is no negative significant correlation. The $p = 0.001 < 0.01$ coefficient of the relationship between the consumer perceived value and consumer willingness is 0.361, indicating that there is a positive and significant correlation. To sum up, the preliminary assumptions 2 and 6 do not hold, and the assumptions 3–5 and the assumptions 7 and 8 hold.

We have discussed the correlation between the characteristics of new media communication and consumers' willingness. Next, we will discuss and analyze the correlation between the two. The results are shown in Table 4.

It can be seen from Table 4 that the relationship $p = 0.001 < 0.01$ between consumer willingness and consumer behavior has a coefficient of 0.781, indicating that there is a positive and significant correlation between the two and the correlation is extremely strong.

4.3.2. Multiple Stepwise Regression Analysis between Correlated Variables. Correlation analysis mainly tests whether there is a relationship and the degree of correlation between variables. Regression analysis can not only test the positive and negative relationship between variables but also test the change law between variables, and find the most important influencing factors. Therefore, this paper adopts the multiple stepwise regression analysis method to test the hypothesis. The larger the R value, the better the model; $R > 0.4$ is generally considered better. We have tested the correlation

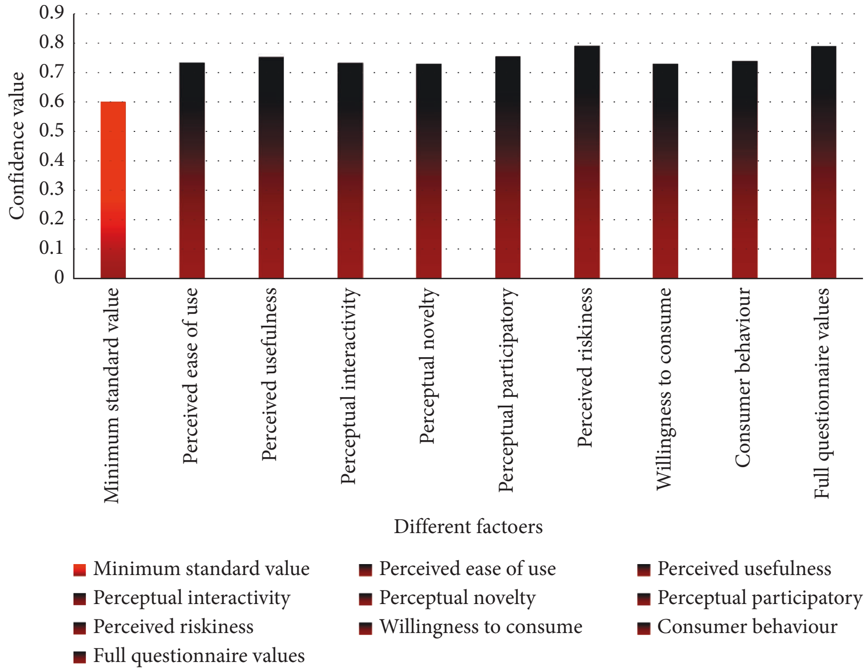

Figure 7: Graphs of the results of the different factor reliability tests.

Table 2: Questionnaire reliability analysis data table.

Variable name	Name of issue	Factor loadings	Eigenvalue	KMO	Cumulative variance contribution	Bartlett
Perceived ease of use	1	0.821	2.147	0.622	64.031	0.000
	2	0.712				
	3	0.645				
Perceived usefulness	1	0.789	2.321	0.722	55.321	0.000
	2	0.786				
	3	0.632				
	4	0.712				
Perceptual interactivity	1	0.717	2.489	0.621	61.054	0.000
	2	0.821				
	3	0.751				
	4	0.632				
Perceptual novelty	1	0.745	2.532	0.711	62.781	0.000
	2	0.823				
	3	0.667				
Perceptual participatory	1	0.834	2.117	0.678	50.12	0.000
	2	0.721				
	3	0.656				
Perceived riskiness	1	0.852	2.187	0.617	70.123	0.000
	2	0.921				
	3	0.756				
Consumer wishes	1	0.765	2.421	0.651	76.478	0.000
	2	0.932				
Consumer behavior	1	0.850	2.645	0.687	59.357	0.000
	2	0.762				

between perceived usefulness, perceived ease of use, perceived interactivity, perceived novelty, perceived value, and consumer willingness. Next, we use a regression model to analyze the causal relationship between consumer willingness and new media communication factors. Its independent variables are perceived usefulness, perceived ease of use, perceived interactivity, perceived novelty, and perceived value. The intermediate variable is consumer willingness. The demonstration results are shown in Tables 5 and 6.

It can be seen from Table 5 that $R = 0.735$ in the regression model, and its value is greater than 0.4, indicating that the established model is feasible. The value of Sig. of the

Table 3: Data table of correlation analysis between various factors of new media communication and consumers' willingness.

		Perceived ease of use	Perceived usefulness	Perceived interactivity	Perceived novelty	Perceived engagement	Perceived riskiness	Perceived value
Consumer wishes	Pearson correlation	0.387**	0.587**	0.551**	0.651**	0.213**	−0.183*	0.361**
	Salience	0.011	0.000	0.017	0.046	0.053	0.052	0.000
	N	92	92	92	92	92	92	92

Note. "*" indicates a significant correlation at the 0.05 level, and "**" indicates a significant correlation at the 0.01 level.

Table 4: Data sheet on the correlation between consumer intention and consumer behavior.

		Consumer wishes
Consumer behavior	Pearson correlation	0.781**
	Salience	0.000
	N	92

Table 5: Analytical data sheet for perceived usefulness, perceived ease of use, perceived interactivity, perceived novelty, perceived value, and consumer intention.

Model ANOVA	Sum of squares	df	Mean square	*F*	Sig
Return	41.113	4	10.381	50.12	0.000
Residual	39.567	87	0.210		
Statistics	80.68	91			
Model regression analysis	R	R Square	Adjust R-square	Standard estimate error	
1	0.735	0.540	0.519	0.469	

Table 6: Table of regression coefficients and significance coefficients.

	Models	Coefficient: Non-standardized coefficients		Standard coefficient	*t*	Sig
		B	Standard error	Trial version		
1	Constants	0.301	0.252		1.21	2.321
	Perceived ease of use	−0.004	0.057	−0.004	−0.081	1.210
	Perceived usefulness	0.217	0.071	0.216	2.518	0.021
	Perceptual interactivity	0.273	0.077	0.241	3.393	0.000
	Perceptual novelty	0.414	0.062	0.411	6.545	0.035
	Perceived value	0.378	0.061	0.378	5.415	0.000

model is 0.000, indicating that the model is statistically significant. Overall, the established analytical model is valid. It can be seen from Table 6 that the significance values of perceived ease of use and constants are both greater than 0.05, indicating that they are not significant. Therefore, excluding these two variables, the resulting regression formula should satisfy:

$\mathrm{Y(Consumerwillingness)} = 0.378\mathrm{X(Perceivedvalue)} + 0.411\mathrm{X(Perceptual\ novelty)} + 0.241\mathrm{(Perceptual\ interactivity)} + 0.216\mathrm{(Perceived\ usefulness)}$.

It can be seen from the formula that the main factors affecting consumers' willingness are perceived novelty, perceived value, perceived interactivity, and perceived usefulness. h Hypothesis 3, Hypothesis 5, Hypothesis 7, and Hypothesis 8 hold.

In the analysis process, we first analyze the independent variables and intermediate variables and then analyze the intermediate variables and dependent variables. The dependent variable in this paper is consumer behavior. Therefore, the next step is to perform regression analysis on the dependent variable and the intermediate variable, and the analysis results are shown in Tables 7 and 8.

It can be seen from Table 7 that $R = 0.713$ in the regression model, and its value is greater than 0.4, indicating that the established model is feasible. The value of Sig. of the model is 0.000, indicating that the model is statistically significant. Overall, the established analytical model is valid. As can be seen from Table 8, the significance of the two variables of constant and consumer willingness are both less than 0.05, indicating that these two variables are statistically significant. The resulting regression model formula should satisfy:

$Y\mathrm{(Consumer\ behavior)} = 0.641\mathrm{X(Consumer\ willingness)} + 1.564$.

It can be seen from the formula that 0.641 is a positive value, indicating that the influence of consumer willingness on consumer behavior is positive. It shows that Hypothesis 1 is true. In summary, through correlation analysis and regression analysis, the results are shown in Table 9.

Table 7: Data analysis table for consumer intentions and consumer behavior.

Model ANOVA	Sum of squares	df	Mean square	F	Sig
Return	31.215	4	30.154	121.766	0.000
Residual	48.787	88	0.231		
Statistics	80.68	92			
Model regression analysis	R	R Square	Adjust R-square	Standard estimate error	
1	0.713	0.508	0.499	0.459	

Table 8: Table of regression coefficients and significance coefficients.

		Coefficient				
Models		Non-standardized coefficients		Standard coefficient	t	Sig
		B	Standard error	Trial version		
1	Constants	1.561	0.203	1.564	7.654	0.001
	Perceived ease of use	0.651	0.049	0.641	10.865	0.000

Table 9: Summary of research hypothesis results.

Assumption number	Assumed content	Assumed results
A1	The usefulness of new media has a positive impact on consumer behavior	Established
A2	The participatory nature of new media has a positive impact on consumer behavior	Not established
A3	The interactive nature of new media has a positive impact on consumer behavior	Established
A4	The ease of use of new media has a positive impact on consumer behavior	Not established
A5	The novelty of new media has a positive impact on consumer behavior	Established
A6	The risky nature of new media negatively affects consumers' consumer behavior	Not established
A7	The greater the value of the goods posted on the new media platform, the more it has a positive impact on consumer behavior	Established
A8	The usefulness of new media has a positive impact on consumer behavior	Established

5. Conclusion

In recent years, with the improvement and development of new media technology, more and more people prefer to use new media platforms for consumption. In this environment, it is imperative to study the impact of new media communication on consumer behavior. This paper explores the influencing factors of consumers in the context of new media communication. Combined with relevant literature, the corresponding hypotheses are put forward, and experimental data are obtained by means of questionnaires. Then, an analysis model is built with the help of the industrial edge cloud deployment algorithm, and the hypothesis is analyzed, and a feasible conclusion is drawn. The main research work of this paper is divided into the following three points:

5.1. Industrial Edge Cloud Algorithms and Related Theories of New Media. This part introduces theoretical research on new media and industrial edge cloud deployment successively. It focuses on the description of the characteristics of new media communication and provides theoretical basis for the following assumptions. At the same time, the theoretical research of industrial edge cloud deployment is also introduced, which provides a theoretical basis for the subsequent model construction.

5.2. Model Construction and Assumptions Made. This part compares and analyzes the ACR, SER, and ELDR indicators between the algorithm in this paper and other algorithms. Then, an analysis model is constructed based on the characteristics of the algorithm. On the basis of the previous new media communication theory, eight hypotheses are put forward, and the variable design of the questionnaire is carried out.

5.3. Experimental Analysis of the Impact of New Media Communication on Consumer Behavior. In this part, the statistical analysis of the data of the experimental subjects is carried out, and the reliability and validity of the survey content of the questionnaire are analyzed. Then, correlation and regression analysis were performed between the variables. According to the experimental analysis results, the functional relationship of influencing consumer factors is obtained, and the authenticity of the previous assumptions is tested at the same time. Most of its assumptions are in line with expectations, and the magnitude of the influencing factors can be obtained based on the relationship.

Due to the influence of the experimental environment, the number of questionnaires distributed and recovered in the article is not large enough, which will cause errors in the judgment of the current situation of new media communication. If there is not enough content and the selected indicators are not perfect, it may affect the final experimental results. In view of the above deficiencies, it is also the focus of future work improvement.

Data Availability

The experimental data used to support the findings of this work can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest in our work.

Authors' Contributions

All authors have seen the manuscript and approved to submit to the journal for publication.

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