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Information Entropy Algorithm-Based Marketing Effectiveness Evaluation of Social Platforms Driven by Digital Economy

Jian Tang[1,*]

[1] School of Management, Yangzhou Polytechnic University, Yangzhou, Jiangsu, 225009, China

SUMMARY: *In the age of digitization, social media has become one of the main catalysts of marketing evolution for businesses because of their broad reach. For effective evaluation of social media marketing efficiency, this research paper proposes an evaluation framework based on three aspects: brand communication, user interaction, and sales conversion. Based on the combination of information entropy and uncertainty measurement theory, a model of social media marketing effectiveness is created. The marketing performance will be classified and rated based on confidence identification. In this research, Weibo, WeChat, Xiaohongshu, and Douyin were selected as research objects, and the research will investigate consumer satisfaction and preferences regarding social media marketing activities by using questionnaires and perform an overall evaluation of the marketing effectiveness of a specific turkey noodle brand. There is a significantly strong positive correlation (P<0.05) between social media marketing efficiency, brand communication, user interaction, and sales conversion. 68.81% of consumers showed satisfaction or high satisfaction with social media marketing activities. Sales conversion exerted the greatest influence (39.51%) on social platform marketing effectiveness. The social platform marketing evaluation system enables precise assessment of brand marketing proficiency. Enhancing social platform marketing effectiveness requires further optimization of marketing deployment strategies and innovative content creation aligned with the "3*3" principle.*

KEYWORDS: *social media platforms; marketing effectiveness; information entropy; uncertainty measure; confidence level*

1 Introduction

Throughout the history of the world's economic development, every scientific and technological revolution will greatly promote the social and economic leap. In recent years, with the popularization of the Internet and mobile Internet technology, mankind has entered the era of digital economy mainly characterized by the application of new-generation information technology, such as cloud computing, Internet of Things, and big data [1]. Traditional enterprises have changed from product-centered, relying on competitive means such as spelling scale, speed, and price, to personalized, flexible, and precise production centered on constantly meeting consumer needs, mainly relying on competitive means such as quality and service [2-4]. Returning to the essence of business, reshaping the enterprise marketing system with consumers as the core, prompting the realization of benign interaction between enterprises and producers, and providing consumers with the best quality service [5]. In this context, more and

*tj150525@163.com
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more traditional enterprises realize that with the help of the traditional marketing model can no longer cope with the fast-changing market in today's world, and enterprises must reconstruct their marketing model to cope with the rapidly changing personalized needs of consumers in the context of the Internet.

With the continuous advancement of technology, social networking services (SNS) have experienced rapid growth, emerging as the most user-dense, influential, and commercially valuable online platforms [6]. By December 2024, Facebook's monthly active users reached 3 billion, marking a 5% year-over-year increase. During the same period, China's mainstream social platforms Weibo and WeChat saw their monthly active users grow to 500 million and 1.2 billion respectively [7]. In today's world, social platforms have become essential elements in the course of everyday life, serving as necessary application platforms providing users with entertainment services, mobile shopping services, information searches, and video chat [8, 9]. The platforms serve individualized demands regarding apparel, foodstuff, accommodation, and transportation. As the number of users increases significantly, the potential business benefits associated with these platforms become apparent over time. Currently, advertisements online through social platforms are rather common. Using these platforms as a tool to promote brands has become the most effective way of building brand images among many multinationals like Procter & Gamble, Google, General Motors, and Dell. In contrast, Chinese society has been slower in adopting social media marketing compared to that in other countries. Despite the recognition of the economic value of the social platforms, their comprehension of it has been inadequate due to the lack of an appropriate theory in this field.

Marketing channel research uses mainly marketing theories. With the increasing depth of study in the field of channel research, multi-channel marketing has been gradually recognized as one of the present-day hotspots for researchers. Chen, I et al. [10] suggested that owing to differences between channel members, various strategies have to be developed in the multi-channel member management approach. In a company's choice of a channel system, it is the process and functions that affect it and determine the purpose of channel [11]. The best choice of marketing channels for a company therefore lies in fulfilling the requirements of target customer groups while investing as little cost as possible. When it comes to the relationship influence issues of marketing channels, Martin-Herran, G et al. [12] explored the two faces of pricing in the marketing channel. Through their dynamic channel strategy, they incorporated consumer price perception, price perceived quality evolution, and strategic interaction of channel members together into one theory. In Palmatier et al., [13] a very unique channel marketing system was introduced which involves attracting customers through various channels and thus providing a sound theoretical foundation for marketing channels. In Paswan et al., [14], the relationships between three different types of marketing strategies such as aggressive marketing, price leadership, and product specialization and their relationship with relationalism in the marketing channel were analyzed. They found a positive relationship between aggressive marketing and price leadership with relationalism whereas negative correlation was found between product specialization and relationalism. Further, Ozyirmidokuz et al., [15] used data mining techniques to collect data regarding the marketing channels in multinational firms and suggested decision rules and an accurate method for complaint prediction in the marketing channel. Marketing channel management is a difficult process. With the advent of e-finance through the internet and the dispersion of consumers, a number of manufacturers use multiple channel marketing systems [16]. Marketing budget and channel marketing efficiency of marketing budgets were discussed in Cai and Choi [17]. Through analyzing risk preferences of members of supply chains and its impact on marketing investment, they found that integrated omnichannel marketing effectiveness is of prime importance.

With the growing significance of marketing channels, the channel evaluation, which is an integral part of channel management, has attracted many researchers and professionals' attention recently. According to Pagán, R. and Malo, M. [18], when many aspects can characterize the channel members' capabilities, some of the main elements usually include market share, sales amount, sales growth rate, operating profit, customers' satisfaction, and customers' complaints rate. Wibowo, A et al. [19] classified social media marketing communications in five categories, including entertainment, interaction, trends, customization, and word-of-mouth. The marketing effectiveness was studied based on such levels as perception, thoughts, emotions, actions, and associations, combining the aspects of marketing campaign with the customer experiences to form a multidimensional framework. Goyal, P et al. [20] established the fact that sustainability integration in the company's performance evaluation process positively affects the development quality, resulting in the addition of the sustainability aspect to marketing performance evaluation processes. Niemand, T et al. [21] applied a structural vector autoregression analysis to evaluate the factors impacting the effectiveness of sales channels of products with high levels of engagement, studying channel interactions and their impact. Finally, Villa, A. and Taurino, T. [22] investigated the performance evaluation in SME marketing from the strategic point of view through KPIs integration with the Balanced Scorecard approach.

A number of assessment methodologies including the Delphi technique, the Analytic Hierarchy Process (AHP), weighted summation methodology, the grey correlation evaluation approach, and the fuzzy analysis and synthesis approach have been widely used in assessing the effectiveness of marketing channels by researchers. Salah, O and Ayyash, M [23] studied the adoption of e-commerce by SMEs and its effect on marketing performance. They utilized Partial Least Squares Structural Equation Modelling (PLSSEM) to analyze their data where they considered the effect of exogenous, mediators, and endogenous variables based on a sample size of 305 SMEs. Haibo, Z and Mingxia, W[24] used Fuzzy Comprehensive Evaluation (FCE) approach to measure the non-quantifiable factors in business marketing channels to provide a quantitative and consistent means of measuring channel effectiveness. Wang, H[25] used ANN and the BPNN to establish a fuzzy comprehensive evaluation model to assess the effectiveness of multi-channel marketing approaches for companies. Motlagh, P and Nasiri, G[26] studied the pricing policy and coordination strategies in dual channel supply chain management based on a mixed integer nonlinear programming framework. Using the Analytic Hierarchy Process (AHP), Wang, C and Hao, X [27] developed an extensive evaluation model of marketing effectiveness based on four objective levels. In their paper, they evaluate the effectiveness of search engine marketing (SEM), hoping that it will provide scientific basis for making decisions about the application of SEM. Cao, G and Weerawardena, J [28] analyzed social media applications from the aspect of market perception and customer linkage capabilities, which affect firm performance. In their analysis, market perception and customer linkage capabilities positively influence marketing performance, which further impacts financial performance. A comprehensive online marketing effectiveness evaluation model based on the four elements of marketing mix (product, price, place, and promotion) together with website quality was suggested by Tsai, W et al. [29]. A method that evaluates incremental contribution of marketing channels based on individual-level data in the online world was introduced by Li, H and Kannan, P [30], and its validity was confirmed by field study. The study proved that the method has huge potential in improving marketing strategies. A marketing channel effectiveness evaluation method using MCDM technology to help marketers choose proper marketing channels was developed by Khatwani, G et al. [31].

With the rise of marketing in social platforms, there is now more freedom to the consumers when purchasing products due to the lack of constraints temporally and spatially that were previously there, thereby providing options and consistently altering the consumers' consumption ideas and practices. After analyzing social platforms' marketing model based on the digital economy, an evaluation index system for the consumer behavior changes and interaction form changes on the social platforms is designed. This is done through the introduction of information entropy algorithm combined with uncertainty measurement theory in constructing the social platforms marketing effect evaluation model. The principle of confidence identification decides the grading and ranking. Four types of social platforms are chosen for the research, where data collection through the use of questionnaires is done. Through the application of linear regression analysis, marketing outcome influencing factors in social platforms are determined. Satisfying and preferred interactions of consumers concerning the marketing activities conducted are analyzed, leading to the evaluation of the turkey noodle brand.

2 Social Media Platform Marketing Effectiveness Evaluation System

The marketing strategy of using social platforms in the digital economy involves the use of social platforms to promote the business and market its brands in the context of the current advanced state of internet technology. The strategy involves the application of technology and platforms like social media, SEO, email marketing, and online advertisements to market a brand and attract more customers to purchase products. Due to advancements in the digital economy, consumer purchasing behavior and information gathering process have changed significantly. Thus, businesses need to assess the efficacy of using social platforms marketing quickly.

2.1 Social Marketing Driven by the Digital Economy

2.1.1 Changes in Consumer Behavior

It is evident that the evolution of consumer behavior in the digital economy era has turned out to be a multifaceted, systematic, and complex phenomenon as a reflection of technological progress impacting the overall consumption ecosystem. On a macro level, with the popularity of online purchases and mobile devices, the way consumers used to shop has changed dramatically as it goes beyond the limits of time and space and restructures the whole consumption ecosystem, encompassing consumers' information acquisition process, decision-making process, and transaction process. In 2024, online sales reached over 15 trillion yuan as China witnessed another year in a row as the biggest online retail country in the world. The statistic not only shows the prosperity of China's e-commerce industry but also implies consumers' strong acceptance of such digital consumption approaches.

From being just communication tools, mobile devices have become intelligent terminals of the consumers. They help consumers develop fragmented, socialized, and personalized consumption behaviors because of their advantages of convenience and immediate actions. Inside the mobile internet environment, consumers are not passive information absorbers anymore as they also actively create contents and spread contents. New consumption platforms such as social media, live commerce, and short videos use algorithms to realize the effective match between consumer behavior touchpoints based on the accurate users' profiles. On the other hand, consumers' decision making process and value judgment process are transformed by such a digital approach as well [32].

2.1.2 Social Media Marketing Engagement

The advent of digital social media platforms has enhanced the ease of interpersonal interaction and information dissemination among consumers. The use of social media channels for buying and selling is gaining more importance, and consumers actively provide feedback about their shopping experiences by leaving comments on social media. Besides, consumers are influenced by recommendations provided by friends and family members and also by opinion leaders. Social media creates a herd effect among consumers. Digital word-of-mouth has now become an important driving force behind consumer decisions. Thus, brands need to effectively utilize the power of social media platforms in marketing by implementing influencer marketing strategies and collaborating with KOLs (key opinion leaders). They should develop engaging topics and create high-quality content that can go viral and achieve brand popularity.

Consumers conduct thorough searches using search engines and online price comparison platforms to assess whether the product delivers value for money. Due to the advent of online review systems, consumers' decisions are becoming increasingly rational, and there is a decline in impulsive purchases and blind following. Thus, it is imperative for organizations to shift focus back to their core products/services when undertaking marketing campaigns. Focusing on providing top-notch consumer experiences can help businesses gain market leadership through positive word-of-mouth.

2.2 Social Media Platform Marketing Effectiveness Evaluation System

2.2.1 Evaluation Indicator System Framework

Under the influence of the digital wave, corporate brand content marketing has shifted from its traditional form of unidirectional communication to an innovative model based on interactivity and experience. At the same time, due to the fragmentation of the social media context, it is difficult to concentrate attention on social media, which brings difficulties to the application of brand content marketing. The problem of the quantification of ROI and volatility of communication becomes prominent. Hence, the research in the area of evaluation and optimization becomes particularly meaningful [33].

Based on current research and following the principles of scientificity, systematicness, operability, and measurability, a marketing effectiveness evaluation system on the social platform will be established as seen in Table 1. The evaluation system will include both primary and secondary indexes, where the primary indexes mainly involve three core elements: brand communication effectiveness, user interaction effectiveness, and sales conversion effectiveness. Among them, brand communication effectiveness evaluates the reach of the content dissemination; it shows the extent to which the brand message can spread to the target audience. User interaction effectiveness analyzes the level of audience participation in the content dissemination, showing the degree of connectivity between the brand and users.

Table 1: Evaluation system for marketing effectiveness on social platforms

Primary indicator	Secondary indicator	Code
Brand communication effect	Exposure volume	B1
	Reading volume	B2
	Reach rate	B3
User interaction effect	Number of likes	U1
	Number of comments	U2
	Number of shares	U3
	Number of collections	U4
	Fan growth number	U5
Sales conversion effect	Click conversion rate	S1
	Clue acquisition volume	S2
	Product sales volume	S3
	Return on investment	S4

2.2.2 Evaluation Grade Classification Criteria

In order to make sure that social media marketing efficiency evaluation is objective and holistic and based on previous research of marketing efficiency evaluation, the performance level of social media marketing can be appropriately graded from Grade I to Grade V, including excellent, good, moderate, poor, and very poor, respectively. The performance levels are measured according to the total score of social media marketing efficiency evaluation: [0,2], (2,4], (4,6], (6,8], and (8,10].

Using the grading system, the advantages and disadvantages of the social media marketing efficiency can be found.

3 Social Media Marketing Effectiveness Evaluation Model

With the rapid advancement and widespread adoption of information technology, digital technologies have become a key driver of innovation and transformation across all industries. As the internet and mobile devices become ubiquitous, online marketing supported by social media platforms has become an indispensable part of the modern business landscape. Currently, corporate digital marketing faces real challenges such as inadequate marketing capabilities on social media platforms, suboptimal user experiences, and insufficiently refined marketing tactics, which directly limit the effectiveness of corporate marketing efforts. Therefore, a comprehensive evaluation of social platform marketing performance is necessary to assist enterprises in better implementing their social platform marketing strategies.

3.1 Information Entropy and Uncertainty Measure Theory

There are p evaluation subjects M, meaning the evaluation subject space is $M=\{M_1,M_2,\cdots,M_p\}$. For each evaluation subject $M_s(s=1,2,\cdots,p)$, there are q individual evaluation indicators, meaning the evaluation indicator space is $X=\{X_1,X_2,\cdots,X_q\}$. The evaluation result M_s is then $M_s=\{X_{s1},X_{s2},\cdots,X_{sq}\}$. Here, $X_s(j=1,2,\cdots,q)$ represents the measured value of the j th evaluation indicator X_j for M_s. The measured values of evaluation indicators x_{sj} are divided into n grades, forming an evaluation grade space of $C=\{C_1,C_2,\cdots,C_n\}$. Here, $C_r(r=1,2,\cdots,n)$ denotes the r th evaluation grade. The r th quality grade is defined as "higher" than the $r+1$ th grade, denoted as $C_r>C_{r+1}$. If $C_1>C_2>C_3>\cdots>C_n$, then $\{C_1,C_2,\cdots,C_n\}$ is considered an ordered partition class of C.

3.1.1 Single-Indicator Measurement Evaluation Matrix

First, strictly define the grading criteria based on the evaluation level. For Level C_1 indicators, characteristic values are expressed as interval numbers, with the lower bound serving as the Level C_1 criterion. For Level C_r indicators, the upper bound of the interval is adopted as the Level C_r criterion. For Level $C_2,C_3,\cdots C_{r-1}$ indicators, the median of the interval is used as the classification standard. Establish a single-indicator measure function $\mu(x_{sj}\in C_r)(s=1,2,\cdots,p;j=1,2,\cdots,q)$. If $\mu_{ijr}=\mu(x_{sj}\in c_r)$ represents the membership degree of x_{sj} for the r th evaluation level C_r, and satisfies the following conditions:

$$0 \le \mu(x_{sj} \in c_r) \le 1 \tag{1}$$

$$\mu(x_{sj} \in c) = 1 \tag{2}$$

$$\mu \mid x_{sj} \in \bigcup_{r=1}^{k} C_r \mid = \sum_{r=1}^{k} \mu(x_{sj} \in C_r), (k = 1, 2, \cdots, n) \tag{3}$$

Then μ is termed an unidentified measure, abbreviated as measure. Specifically, equation (1) is referred to as non-negativity and boundedness, equation (2) is termed μ satisfying "normalization" for the evaluation space, and equation (3) is termed μ satisfying "additivity" for the evaluation space.

Second, based on the single-indicator measurement function, calculate the measurement values μ_{ir} for each indicator of evaluation object M_s using the following method. Suppose the evaluation value x_{sj} of the j rd evaluation indicator for the sth evaluation object belongs to the C_r th category of uncertain measurement $\mu_{sjr} = \mu(x_{sj} \in C_r)$. We may assume $a_{j1} < a_{j2} < \cdots < a_{jn}$ (where a_{ji} is the graded standard value $(i = 1, 2, \cdots, n)$). then when $x_{ij} \le a_{j1}$, take $\mu_{jn} = 1$, with all other measurement values set to 0; when $x_i \ge a_{jn}$, take $\mu_{sj1} = 1$, with all other measurement values set to 0; when $a_i \le x_i \le a_{d+1}$, construct a linear function according to the definition of uncertain measurement, namely:

$$\mu_{ijl} = \frac{1}{a_{jl+1} - a_{jl}} (a_{jl+1} - x_{sj}) \tag{4}$$

$$\mu_{sjl+1} = \frac{1}{a_{jl+1} - a_j} (x_j - a_j); \mu_{jk} = 0 \tag{5}$$

When $k < l$ or $k > l + 1$, where $1 < l < n$.

The matrix formed by the metric values μ_{sjr} obtained from the above calculations is:

$$(\mu_{gr})_{q \times a} = \begin{bmatrix} \mu_{s11} & \mu_{s12} & \cdots & \mu_{s1n} \\ \mu_{s21} & \mu_{s22} & \cdots & \mu_{s2n} \\ \vdots & \vdots & & \vdots \\ \\ \mu_{s1} & \mu_{s2} & \cdots & \mu_{sqn} \end{bmatrix} \tag{6}$$

In the formula, $(\mu_{sjr})_{q \times n}$ represents the single-indicator measurement evaluation matrix.

3.1.2 Information Entropy Weighting Method

Using the entropy weight method to calculate the weights of evaluation indicators can reduce the influence of subjectivity. As an objective weighting approach, the entropy weight method offers significant advantages in its high precision and objectivity. Compared to subjective weighting methods, the entropy weight method is virtually unaffected by human bias, thereby ensuring the accuracy and practical relevance of evaluation outcomes. As such, the characteristic contributes to making the entropy weight approach generate more trustworthy and credible assessment results in various situations.

Let $u(x)$ be a function from 0 to 1 satisfying the normalization condition. Let the i nd primary evaluation indicator be Q_i, and the j th secondary evaluation indicator under it be Q_{ij}. Let the measurement vector corresponding to the j th secondary evaluation indicator Q_{ij} under a certain primary evaluation indicator Q_i for the evaluation object be $\mu_{ij} = (\mu_{ij}^{(1)}, \mu_{ij}^{(2)}, \cdots, \mu_{ij}^{(k)})$, satisfying the normalization condition, i.e.:

$$\sum_{k=1}^{K} \mu_{ij}^{(k)} = 1 \tag{7}$$

In the formula, $\mu^{(k)}$ denotes the evaluation indicator, and Q_{ij} represents the membership degree belonging to category k, denoted as $\mu_{ij}^{(k)} \in [0,1]$. Its value reflects the contribution of this secondary evaluation indicator to each risk level.

By arranging the measurement vectors of all secondary evaluation indicators in columns, the uncertain measurement matrix M_i under a single primary evaluation indicator is obtained as follows:

$$M_i = \begin{bmatrix} \mu_{i1}^{(1)} & \cdots & \mu_{i1}^{(K)} \\ \vdots & \vdots & \vdots \\ \mu_{in}^{(1)} & \cdots & \mu_{in}^{(K)} \end{bmatrix} \tag{8}$$

In the formula, n represents the number of secondary evaluation indicators contained under this primary evaluation indicator.

The measurement vector form for a single secondary evaluation indicator is:

$$\mu_{ij} = (\mu_{ij}^{(1)}, \mu_{ij}^{(2)}, \cdots, \mu_{ij}^{(K)})^T \tag{9}$$

If a system or process possesses a certain probabilistic nature, its entropy value reflects the uncertainty or disorder inherent in that probability distribution [34]. The formula for calculating entropy is:

$$H_{ij} = -\sum_{k=1}^{K} \mu_{ij}^{(k)} \ln(\mu_{ij}^{(k)}) \tag{10}$$

In the formula, H_{ij} represents the information entropy of the secondary evaluation indicator Q_{ij}, which measures the uncertainty or disorder of a random variable.

Calculate the distinctiveness n_{ij} of each secondary evaluation indicator and perform normalization, then:

$$v_{ij} = 1 - \frac{H_{ij}}{\ln K} \tag{11}$$

In the formula, $\ln K$ represents the maximum entropy value, and K denotes the number of categories.

Finally, the weight ω_{ij} of the secondary evaluation indicator is obtained through the normalized recognition rate v_{ij}:

$$\omega_{ij} = \frac{v_{ij}}{\sum_{j=1}^{n} v_{ij}} \tag{12}$$

In the formula, ω_{ij} represents the secondary evaluation indicator, and Q_{ij} denotes the weight assigned to this primary evaluation indicator.

3.1.3 Multi-Indicator Uncertain Measure

For sample $\upsilon_{ik} = \upsilon(\Gamma_i \in \Re_k)$ to be classified as belonging to the k rd evaluation category $\Re_k$ of Γ_i, the following holds:

$$\upsilon_{ik} = \sum_{j=1}^{m} \omega_j \upsilon_{ik}^{j} (i = 1, 2, \cdots, n; k = 1, 2, \cdots, p) \tag{13}$$

Since $0 \le \upsilon_k \le 1$ and $\sum_k =1^p \upsilon_{ik} = \sum_{k=1}^{p}\sum_{j=1}^{m} \omega_j \upsilon_{kk}^{j} = \sum_{j=1}^{m}\left(\sum_{k=1}^{p} \upsilon_{ik}^{j}\right)$. $\omega_j = 1$, then υ_{ik} is an unknown measure, so there exists a matrix:

$$(\upsilon_{ik})_{n\times p} = \begin{bmatrix} \upsilon_1^1 & \upsilon_1^2 & \cdots & \upsilon_1^p \\ \upsilon_2^1 & \upsilon_2^2 & \cdots & \upsilon_2^p \\ \vdots & \vdots & \ddots & \vdots \\ \upsilon_n^1 & \upsilon_n^2 & \cdots & \upsilon_n^p \end{bmatrix} \tag{14}$$

The above equation represents a multi-objective comprehensive uncertain measure evaluation matrix, where $\{\upsilon_i^1, \upsilon_i^2, \ldots, \upsilon_i^p\}$ denotes the multi-indicator comprehensive measure evaluation vector of Γ_i.

3.2 Confidence-Based Identification Criteria and Ranking

3.2.1 Confidence Level Identification Criteria

Since the levels within the evaluation metric's hierarchical space are arranged sequentially, the maximum measure recognition criterion cannot be used to determine the final evaluation outcome. To obtain the final results for evaluating social platform marketing effectiveness, a confidence determination criterion must be introduced.

Set the reliability to λ ($\lambda \ge 0.5$ typically takes values of 0.6 or 0.7), then the level D_{k_0} of social platform s_i can be determined using the following formula:

$$k_0 = \min|k : \sum_{i=1}^{k} \mu_i > \lambda, k = 1,2,3,4,5| \quad (15)$$

3.2.2 Ranking of Evaluation Subjects

In addition to determining the evaluation grade of the subject, it is sometimes necessary to rank the degree of deterioration. If $C_1 > C_2 > C_3 > \cdots > C_n$, assign a score of F_r to C_r, then $F_r > F_{r+1}$, and:

$$d_s = \sum_{r=1}^{n} F_r \mu_{sr}, (s = 1, 2, \cdots, p) \quad (16)$$

In the formula, d_s represents the unknown importance of evaluation object M_s. Let $d = [d_1, d_2, \cdots, d_p]$ denote the unknown importance vector. Based on the magnitude of d_s, the degradation levels of each evaluation object within the evaluation object space can be ranked.

3.3 Questionnaire Design and Distribution

3.3.1 Questionnaire Design

For this study, we have chosen four popular websites, which include WeChat, Weibo, Douyin, and Xiaohongshu. In addition, we will select the top five stores on the basis of their sales in June 2024.

Our questionnaire will be based on the previously formulated evaluation of social media marketing success to ensure that consumer behavior is analyzed in depth. The questionnaire will consider such factors as brand communication, consumer interaction, and sales conversion. In this way, we will be able to conduct a deeper examination of the situation regarding marketing on social websites. This survey will combine customer attitudes towards the existing situation on social sites with the level of marketing success.

The survey includes consumers who have already made orders through the previously mentioned four social media platforms or live streaming rooms. With this survey, we hope to achieve an understanding of customer perceptions towards social media marketing to develop better optimization strategies. The questionnaire will be separated into two parts, the first of which seeks basic customer information about age, gender, education level, and customer consumption habits to create customer profiles. In the second part, the questionnaire mainly focuses on collecting data regarding customer perceptions of marketing activities on social media platforms concerning brand recognition, customer interest in interactive live stream content, interaction with the company, consumption behavior, and feedback. Consumer satisfaction can be measured from various aspects such as marketing attributes (MY1), store appearance (MY2), prices (MY3), product quality (MY4), service quality (MY5), variety (MY6), experiences (MY7), and marketing effects (MY8). In this survey, scoring is conducted by utilizing a five-level Likert scale, which is rated as 1 to 5 (Strongly disagree, Disagree, Undecided, Agree, and Strongly Agree).

In addition, this study attempts to analyze the consumers' preferences in interacting with the brand on different social media platforms, such as reading (HD1), liking (HD2), commenting (HD3), sharing (HD4), taking part in brand activities (HD5), buying promoted products (HD6), contacting through private messages (HD7), and never participated (HD8).

3.3.2 Distribution of Survey Questionnaires

The time period for the distribution of this questionnaire is expected to be from June to July in 2024. For the implementation stage of our work, a digital distribution approach has mainly been chosen. The link to the questionnaire was produced using the Wenshu Xing platform and was distributed through multiple platforms, including the Wenshu Xing platform, Douyin, and Xiaohongshu, to target certain demographic groups. To ensure that the design of our questionnaire met all scientific criteria, we undertook a preliminary test before distributing the questionnaires. Several problems have been identified while distributing the questionnaires, including mistakes in wordings and misunderstanding among respondents. With the help of our teachers' instructions and extensive research, we finally started distributing the questionnaire through the Wenjuanxing platform.

4 Case Study on Evaluating the Effectiveness of Social Media Platform Marketing

As the market economy continues to evolve, innovation and updates in business marketing concepts become an unavoidable trend. Nonetheless, some traditional companies display little enthusiasm regarding the adoption of new marketing ideologies. They usually fail to develop logical marketing strategies, which in turn hampers the efficiency of brand marketing communication and sustainable development of their businesses. Under the impetus of the digital economy, social platform marketing becomes an important element for enterprises to carry out brand marketing innovation. It is only through full recognition of the effects of social platform marketing that the foundation of enterprise brand marketing can be strengthened.

4.1 Questionnaire Evaluation Data Analysis

4.1.1 Scale Reliability Analysis

Reliability analysis helps measure the reliability of a scale. When a questionnaire is designed, an adequate analytical technique must be selected to conduct several tests of the questionnaire. If consistent results are obtained, the questionnaire is scientifically reliable; otherwise, it will lack sufficient reliability. Cronbach's alpha is a typical reliability analysis technique where correlation of various indicators is assessed according to their coefficients. Generally: - If $0.65 < \alpha < 0.75$, then the scale is reliable. - If $0.75 < \alpha < 0.85$, then the scale is highly reliable. - If $\alpha > 0.85$, then the scale is extremely reliable.

SPSS software was applied in the current study to conduct reliability analysis of the survey questionnaire as shown in Table 2 below where CITC stands for total correction item correlation coefficient and Item denotes alpha coefficient of deleted items.

In the questionnaire of the current study, Cronbach's α coefficients in the three dimensions of brand communication, user interaction, and sales conversion are 0.878, 0.885, and 0.839, correspondingly. The reliability analysis shows that the reliability of the questionnaire is at the required level and the survey results obtained through the questionnaire are convergent and reliable. Additionally, all the items had CITC higher than 0.65 meaning they are reliable. Importantly, deleting none of the items increased the value of Cronbach's α. This means that there are no unnecessary items to delete from the questionnaire. In conclusion, the questionnaire of the current study is effective for social media marketing research.

Table 2: The reliability analysis of the questionnaire

Variable	Content	CITC	Item	Cronbach's α
Brand communication effect	Exposure volume	0.702	0.806	0.878
	Reading volume	0.684	0.881	
	Reach rate	0.670	0.892	
User interaction effect	Number of likes	0.662	0.806	0.885
	Number of comments	0.668	0.824	
	Number of shares	0.737	0.830	
	Number of collections	0.721	0.838	
	Fan growth number	0.727	0.819	
Sales conversion effect	Click conversion rate	0.747	0.793	0.839
	Clue acquisition volume	0.695	0.837	
	Product sales volume	0.652	0.826	
	Return on investment	0.683	0.885	

4.1.2 Scale Validity Analysis

In the case of survey questionnaires, besides reliability, additional validity is tested for. For this study, KMO and Bartlett’s Sphericity Tests were done on data obtained from the questionnaire via the SPSS software tool to validate whether the collected data is fit for factor analysis. KMO values lie between 0 and 1, with higher figures denoting greater validity of the questionnaire. A Bartlett’s Sphericity Test measures significant correlation between variables; values lower than the significance level (0.05) signify significant correlation. Table 3 shows results of the KMO and Bartlett’s Sphericity Test. As such, the results demonstrate that KMO sampling adequacy was 0.876 > 0.85 while the significance value of Bartlett’s sphericity test was 0.003 < 0.01 < 0.05. Thus, there was significant correlation among variables, making the data collected fit for factor analysis.

Table 3: KMO and Bartlett spherical test results

Inspection content		Value
The measurement of the suitability of KMO sampling		0.876
Bartlett sphericity test	Approximate chi-square	162.495
	Degree of freedom	263
	Significance	0.003<0.01

The factor analysis process involved the use of SPSS software tool. Results of the total variance explained are depicted in Table 4. In this table, IE, ESS and SSR stand for Initial Eigenvalues, Extraction Squared Loadings, and Rotation Squared Loadings, respectively. Meanwhile, T stands for Total, V represents the percentage of Variance, and C denotes the cumulative percentage. From the analysis using SPSS statistical tool, three factors with initial eigenvalues greater than 1 were identified in the total variance explained results based on the three dimensions of the questionnaire items. Moreover, the cumulative variance accounted for by the top three factors was found to be 67.86% > 60%.

Table 4: The total variance explains the result

-	IE			ESS			SSR		
	T	V/%	C/%	T	V/%	C/%	T	V/%	C/%
1	4.338	36.15	36.15	4.338	36.15	36.15	4.059	33.49	33.49
2	2.529	21.08	57.23	2.529	21.08	57.23	2.894	24.12	57.61
3	1.276	10.63	67.86	1.276	10.63	67.86	1.637	10.25	67.86
4	0.865	7.21	75.07						
5	0.704	5.86	80.93						
6	0.623	5.19	86.12						
7	0.514	4.28	90.4						
8	0.405	3.38	93.78						
9	0.327	2.73	96.51						
10	0.219	1.83	98.34						
11	0.114	0.95	99.29						
12	0.086	0.71	100						

Further orthogonal rotation was performed using the maximum variance method to identify and name common factors. Table 5 presents the component matrix after factor rotation. The results of the rotated component matrix indicate that all three variables in this study could be extracted, with factor loadings exceeding 0.75. Each item effectively corresponds to the variables designed in the questionnaire for this study.

Table 5: The component matrix after factor rotation

Item number		Factor 1	Factor 2	Factor 3
Brand communication effect	B1	**0.762**	0.237	0.254
	B2	**0.839**	0.306	-0.093
	B3	**0.841**	-0.183	0.145
User interaction effect	U1	0.133	**0.732**	-0.157
	U2	0.297	**0.897**	0.245
	U3	0.355	**0.866**	0.238
	U4	0.351	**0.816**	0.399
	U5	0.354	**0.757**	0.134
Sales conversion effect	S1	-0.079	0.088	**0.754**
	S2	0.227	-0.154	**0.776**
	S3	-0.115	0.203	**0.892**
	S4	0.338	0.192	**0.853**

4.1.3 Linear Regression Analysis

Linear regression utilizes regression analysis from mathematical statistics to determine whether two or more variables are correlated, assess the direction and strength of such correlations, and establish mathematical models for predicting variables of interest by observing specific variables. Regression analysis prediction employs regression methods to identify quantitative interdependencies between two or more variables. Regression models enable one to determine the type of correlation between variables and causality among variables.

The following is a correlation analysis using gender, age, educational attainment, and monthly income group as the control variables while the variables in the three categories of brand communication, user interaction, and sales conversion serve as the independent variables.

The social media marketing effectiveness (YX) is used as the dependent variable in order to test the effect of brand communication, user interaction, and sales conversion on social media marketing effectiveness. Figure 1 shows the correlation analysis result of the social media marketing effectiveness.

According to the correlation analysis results, there exists significant positive correlation ($P<0.05$) between social media marketing effectiveness and all the variables of the three categories of brand communication, user interaction, and sales conversion. Correlation coefficients vary between 0.154 and 0.487, providing grounds for further testing for the model regression.

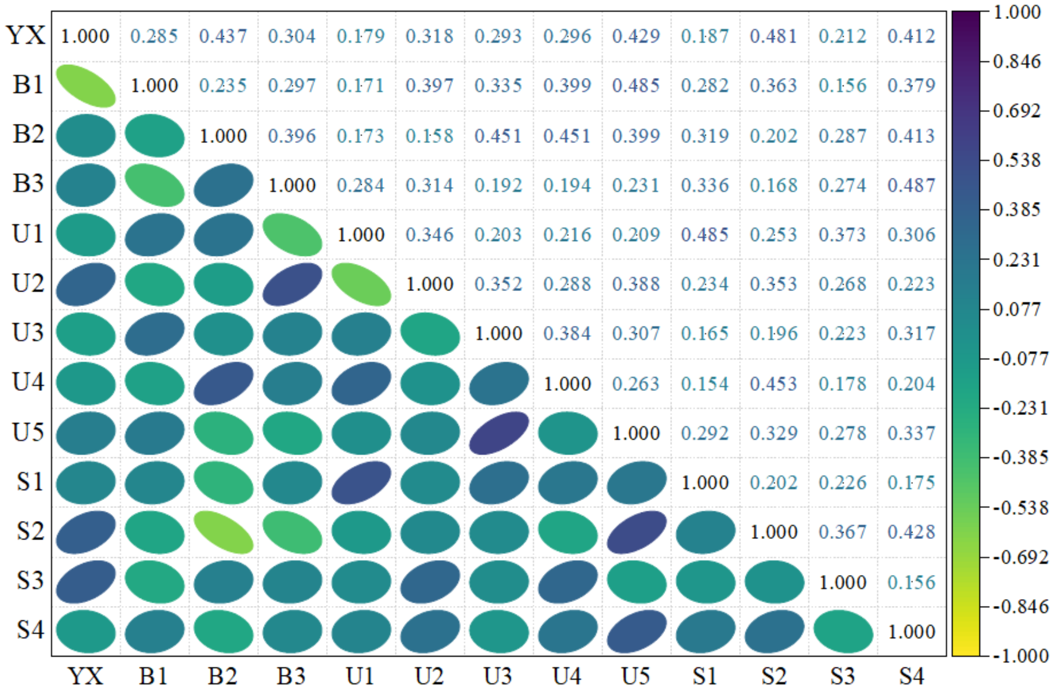

Figure 1: The correlation analysis results of marketing effects on social platforms

Regarding the process of performing the linear regression, there were two main regression analyses, which were undertaken by applying two models in this study, including one without independent variables, while the other with both independent variables and control variables. Table 6 and Table 7 are the results of analysis of variance (ANOVA) and regression analysis.

It can be observed that the adjusted R^2 value of the regression analysis was 0.495. From the ANOVA results, the F-statistic was 32.534 with a probability value below 0.001, which indicated a statistically significant regression relationship. That is to say, the results are statistically significant and fit well.

Regarding the regression coefficients of independent variables, they included 0.253 for brand communication, 0.279 for user interaction, and 0.318 for sales conversion, which were all significantly effective based on their significance probabilities (Sig.) of less than 0.01. It can thus be inferred that both brand communication, user interaction, and sales conversion had a significant positive impact on social platform marketing effectiveness. Furthermore, among these variables, the degree of influence ranked from high to low as sales conversion, user interaction, and brand communication. With the development of digital economy, it will be necessary for business organizations to improve their marketing effectiveness on social media platforms by considering their capabilities of sales conversion and user interaction together with proactive brand communication.

Table 6: Analysis of variance analysis

Model	-	Sum of squares	DF	Equal square	*F*	Sig.	Adj.R^2
1	Regression	72.175	6	15.297	16.328	0.002	0.207
	Residuals	263.538	275	0.758			
	Total	335.713	281				
2	Regression	163.672	9	20.514	32.534	0.001	0.495
	Residuals	172.041	272	0.638			
	Total	335.713	281				

Table 7: The result of Regression analysis

Mode1	Variable	Non-standardized coefficient		Standard coefficient	*t*	Sig.
		Beta	STE			
(1)	(Con_)	-0.514	0.412		-1.251	0.205
	Sex	0.827	0.151	0.318	5.276	0.003
	Age	-0.019	0.094	-0.015	-0.174	0.852
	Edu	0.262	0.083	0.194	3.528	0.000
	Income	0.184	0.072	0.136	2.376	0.028
(2)	(Con_)	-0.885	0.343		-2.663	0.013
	Sex	0.397	0.135	0.145	2.951	0.005
	Age	-0.135	0.078	-0.072	-1.537	0.123
	Edu	-0.058	0.062	-0.038	-0.742	0.468
	Income	0.026	0.069	0.019	0.428	0.674
	B1~B3	0.253	0.045	0.227	3.271	0.000
	U1~U5	0.279	0.072	0.265	6.759	0.002
	S1~S4	0.318	0.056	0.306	4.372	0.000

4.2 User Satisfaction and Interactive Engagement

4.2.1 Consumer Satisfaction

The success of social media marketing is dependent upon the marketing environment established by firms within the social media context. These factors determine consumer behavior, which subsequently affect marketing outcomes. With this in mind, the current research examines constructs that include marketing differentiation, store aesthetics, price, quality, experience, diversity, and marketing effectiveness (MY1-MY8). Figure 2 displays the consumer satisfaction distribution.

Based on the core positioning strategy, the distinctive marketing features adopted by the social media platform to market its products gained relatively high levels of consumer awareness, with 78.65% saying they were highly satisfied or satisfied. In terms of marketing strategies, some issues, such as store design, pricing, product quality, and service quality, performed relatively well, showing high levels of consumer satisfaction within the satisfactory ranges of between 69% and 74%. It should be noted that store design is one of the weaknesses in social media marketing campaigns, as it has received 8.81% dissatisfaction rates from consumers. This means that it is essential to optimize store design when planning marketing on social media platforms at present. Generally speaking, 68.81% of consumers have shown their satisfaction with the marketing activities done by social media, while 18.88% said they were generally average. These results are helpful guidelines for enhancing the performance of marketing on social media.

Consumer experience when they browse through the social media platform not only directly reflects the effectiveness of the marketing campaign and the quality of the products but also indirectly affects brand loyalty and user retention of consumers. The customer experience should be the result of combined efforts of both products and services. With distinctive marketing features, perfect store design, and excellent service details, positive evaluations will be formed by consumers toward the brand. By forming good synergy between products and services, the enterprise can not only satisfy the basic needs of consumers but also bring consumers unexpected benefits, achieving lasting competitive advantages.

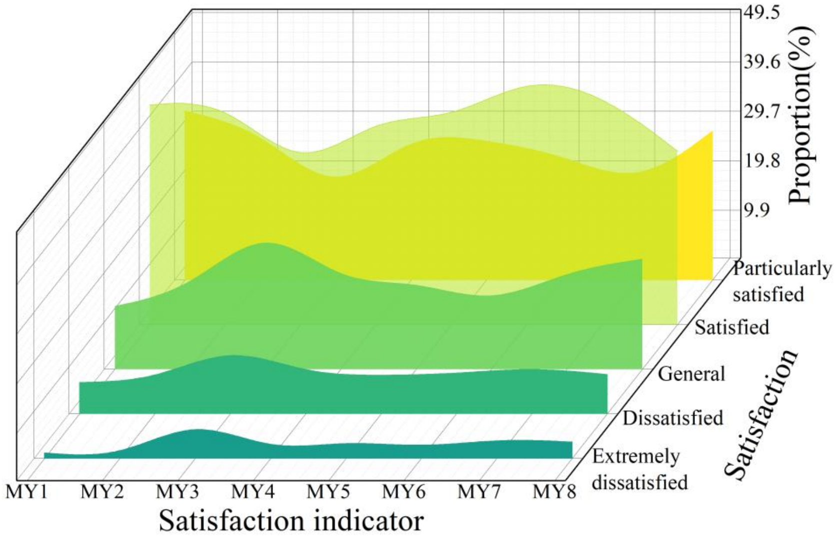

Figure 2: Consumer satisfaction distribution

4.2.2 Social Platform Interaction

Increasing marketing efficiency through social platforms entails frequent brand interaction with users on social media, although such interaction occurs differently depending on the platform. According to the survey results, users' preferences regarding interaction forms were examined for the following activities: reading content by brands (HD1); clicking the 'like' on brand content (HD2); leaving comments on brand content (HD3); sharing brand content (HD4); participation in brand activities (HD5); purchases from promoted products (HD6); interaction via private message (HD7); and never participating (HD8). As is illustrated in Figure 3 below, there are specific user interaction patterns associated with different social media platforms.

From the chart above, it can be seen that there are specific user preferences with respect to brand interaction forms used within particular social media platforms. In this regard, the first activity performed by users on social media includes reading content offered by the brands (HD1), which means that users are primarily active in content consumption. Actions with regards to 'liking' content have a somewhat higher rate when compared to other activities within both Xiaohongshu and WeChat. Users of Douyin display a particularly high degree of willingness to participate in brand activities (HD5), which means that interaction on short video platforms is activity-related. Having the lowest interaction rate with comments among Douyin users means that marketing on Douyin is more suitable for content attraction. Weibo shows high purchase rates from promoted products; thus, marketing on Weibo enjoys good conversion properties. The significantly higher private messaging interaction rate implies that Weibo users tend to receive information or interact with the brand via private messaging. Lastly, the highest rate of content consumption on the WeChat platform confirms that WeChat is still one of the key platforms for content dissemination.

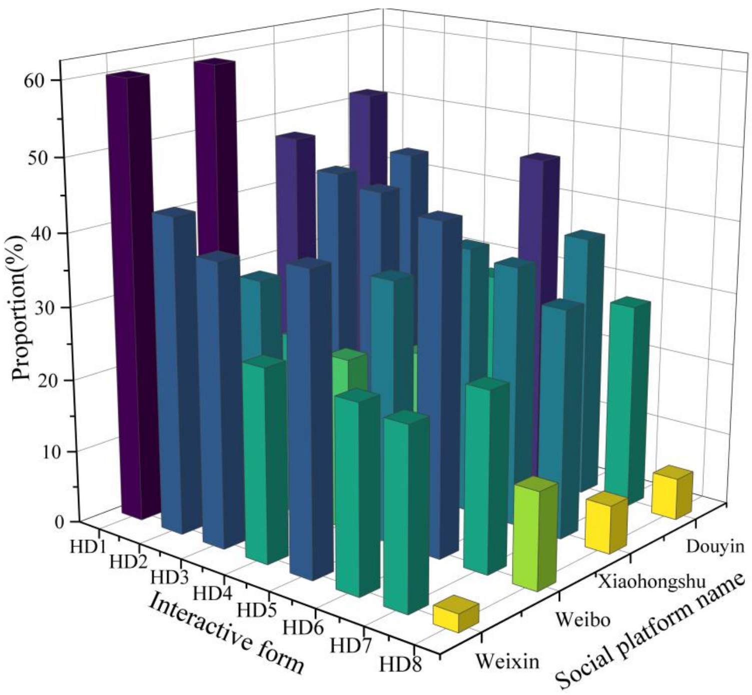

Figure 3: User interaction form preferences

4.3 Evaluation of Social Media Platform Marketing Effectiveness

4.3.1 Evaluation Indicator Weighting

To analyze the efficiency of social media marketing activities, this paper applies the evaluation indicator system formulated above. The research uses questionnaires as an initial data source and incorporates it into the evaluation model of social media marketing efficiency suggested previously. Applying the information entropy algorithm, the weighting factors of each indicator are calculated. At first, the values for all indicators are normalized. Afterward, the application of the entropy weighting approach helps to calculate the weighting factor for each indicator, resulting in the weights of different indicators as illustrated in Figure 4.

The tree diagram of indicator weight distribution demonstrates that among the primary indicators, Sales Conversion Efficiency (S) has the highest impact on social platform marketing efficiency, with the share of 39.51% in the entire weighting. Second comes the indicator User Interaction Efficiency (U) with a share of 33.91%, whereas Brand Dissemination Efficiency (B) has the lowest weighting of 26.58%. Regarding the secondary indicators, Lead Acquisition Volume (S2), Product Sales Volume (S3), and Return on Investment (S4) have the biggest effect on social platform marketing efficiency, with weight values of 0.1021, 0.1036, and 0.0955 correspondingly. In order to improve social platform marketing efficiency successfully, it is vital to pay special attention to the sales conversion results, especially concentrating on the acquisition of leads and sales performance in marketing campaigns. It should be accompanied by an interesting format of user interaction to capture the audience's attention completely and enhance its influence through the promotion of brands, thus retaining users' loyalty.

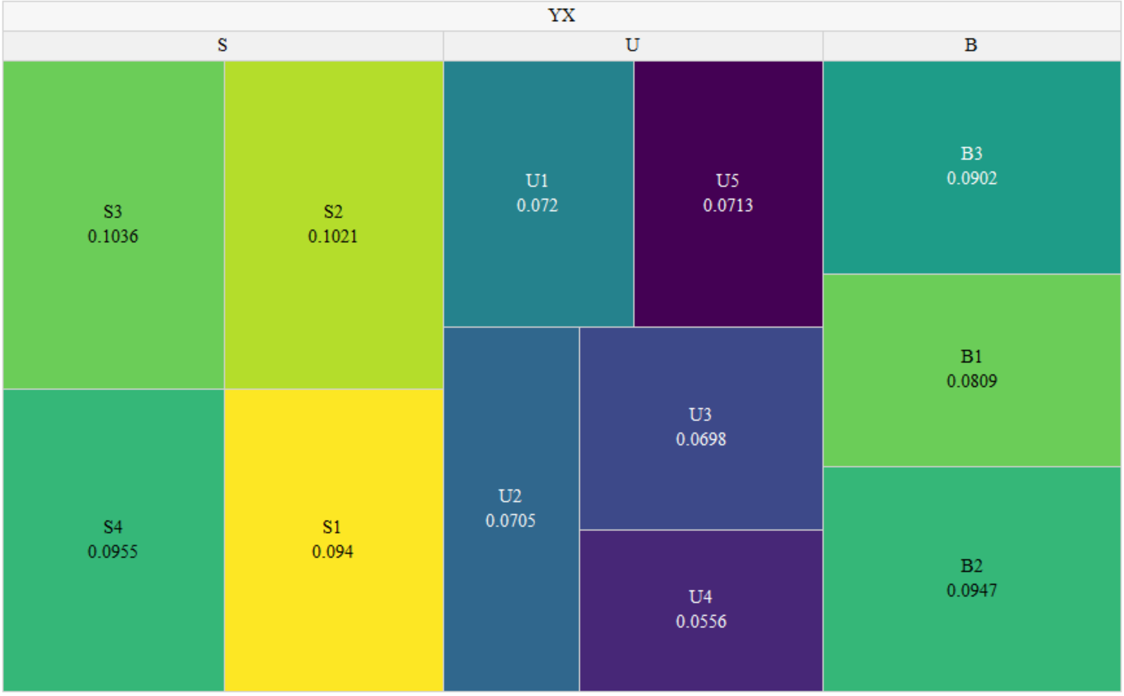

Figure 4: The weights of each evaluation index

4.3.2 Marketing Effectiveness Evaluation

To enhance the effectiveness of social media marketing, this study conducted a comprehensive evaluation of the marketing performance of a certain instant noodle shop on the Douyin platform. A total of 20 consumers who frequently purchase products via Douyin were invited to rate the shop. Based on the scoring criteria outlined earlier, they evaluated the metrics within the social media marketing effectiveness assessment system. The consumer ratings for each metric are presented in Table 8.

Table 8: The scoring results of consumer indicators

-	Code	I	II	III	IV	V
Brand communication effect	B1	0	2	8	6	4
	B2	1	3	7	4	5
	B3	0	2	10	5	3
User interaction effect	U1	2	6	8	1	3
	U2	1	1	12	3	3
	U3	2	3	10	5	0
	U4	0	5	8	3	4
	U5	1	6	7	4	2
Sales conversion effect	S1	3	2	5	8	2
	S2	0	7	9	4	0
	S3	2	5	2	7	4
	S4	1	4	7	3	5

Using the theory of uncertain measures to construct measure functions, the metric measure functions for brand communication effectiveness, user interaction effectiveness, and sales conversion effectiveness can all be expressed as single-metric uncertain measure functions. Consumer metric scores undergo data normalization processing. Based on the normalized results of each metric's scoring data and the single-metric uncertain measure functions, the single-metric measure evaluation matrix for each evaluation metric is calculated as follows:

$$\mu = \begin{bmatrix} 0.00 & 0.10 & 0.40 & 0.30 & 0.20 \\ 0.05 & 0.15 & 0.35 & 0.20 & 0.25 \\ 0.00 & 0.10 & 0.50 & 0.25 & 0.15 \\ 0.10 & 0.30 & 0.40 & 0.05 & 0.15 \\ 0.05 & 0.05 & 0.60 & 0.15 & 0.15 \\ 0.10 & 0.15 & 0.50 & 0.25 & 0.00 \\ 0.00 & 0.25 & 0.40 & 0.15 & 0.20 \\ 0.05 & 0.30 & 0.35 & 0.20 & 0.10 \\ 0.15 & 0.10 & 0.25 & 0.40 & 0.10 \\ 0.00 & 0.35 & 0.45 & 0.20 & 0.00 \\ 0.10 & 0.25 & 0.10 & 0.35 & 0.20 \\ 0.05 & 0.20 & 0.35 & 0.15 & 0.25 \end{bmatrix} \tag{17}$$

Based on the weights assigned to each indicator as specified earlier, namely:

$$\begin{aligned} w = [&0.0809, 0.0947, 0.0902, 0.0720, 0.0705, 0.0698 \\ &0.0556, 0.0716, 0.0940, 0.1021, 0.1036, 0.0955] \end{aligned} \tag{18}$$

Combining the single-indicator measure evaluation matrix and the evaluation indicator weight vector, the comprehensive indicator's unidentified measure vector is calculated and expressed as:

$$\mu = [0.0552, 0.1923, 0.3770, 0.2286, 0.1470] \tag{19}$$

Evaluate the effectiveness level of social media marketing using a confidence criterion, with confidence set at 0.7, based on the calculation results of the uncertain measurement vector derived from the composite indicators. When the membership evaluation level is Level IV, then:

$$\mu_1 + \mu_2 + \mu_3 + \mu_4 = 0.8532 > 0.7 \tag{20}$$

The findings conform to the standard of confidence; thus, it can be concluded that the marketing effectiveness of a particular Yanghuoji Noodle Shop falls into the “good” range. The company constantly introduces different flavors of noodles, meeting the varying tastes of its customers. In addition, it has diversified its marketing activities by using traffic diversion techniques and influencer marketing to create a brand image on the Douyin social media. This business is well-managed and earns good revenue, showing a strong correlation between its performance and evaluation.

4.4 Optimization of Social Media Marketing Strategies

4.4.1 Optimizing Marketing Campaigns

To begin with, develop precision content marketing. With thorough profiling of consumers, e-commerce businesses must take initiative to build differentiated content marketing plans. Work hard to generate personalized marketing contents for different users. Effectively use the technology of data mining to analyze consumer preferences of contents and behaviors and make improvements in content forms and scheduling. Develop effective evaluation systems for the content on social media sites and optimize strategies such as A/B testing. Give much emphasis on producing original content for better engagement and conversions of users. Utilize the advantages of social media sites and produce new forms of contents suitable for each site.

In addition, establish an intelligent ad delivery system. E-commerce firms have to set up intelligent ad delivery systems based on data analysis in order to optimize the allocation of resources. Use machine learning to construct probabilistic models of reaching consumers to make sure that the marketing message is targeted at the right people. Improve marketing strategy by making optimizations through the system of real-time bidding for maximum marketing returns. Develop mechanisms for collaborative deployment of ads on multiple sites where budget allocations are made on the basis of user features and performances. Develop intelligent tools for deploying ads.

4.4.2 Innovative Marketing Content

The innovation of social media marketing content follows the principle of “3×3,” which is to balance the relationship among the proportions of short video contents, live broadcasts, and graphic texts; the proportions of brands’ story-telling, products, and customers’ case studies; and the proportions of professionalism, amusement, and emotions. In particular, it is necessary to create a database for content idea storage and content innovation efficiency evaluation system, that is,

One is to classify and archive the historical excellent contents, and analyze the premium contents regularly to find out the latest topics and summarize the features of popular content elements. Two is to conduct marketing activities in terms of similar themes using different types of contents. Moreover, it is essential to improve the awareness of trends and produce marketing content through combining social hotspots with brands’ features.

5 Conclusion

The research builds an assessment framework of social media marketing effectiveness by using the information entropy and uncertainty measure theories. Through investigating the level of customer satisfaction with regard to four different types of social media marketing campaigns, it seeks to examine the applicability of the proposed evaluation model via real cases. It is found that the effectiveness of marketing on social platforms shows significant positive relationships ($P<0.05$) with all indicator variables in three aspects: brand communication, customer interaction, and sales conversion. Satisfaction or high satisfaction toward social platform marketing activities is indicated by 68.81% of the customers. The impact of sales conversion on the marketing effectiveness of social platforms is highest (39.51%).

About the Author

Jian Tang was born in Yangzhou, Jiangsu, P.R. China, in 1980. I obtained a master's degree from Hefei University of Technology in China. I am currently working at School of Management, Yangzhou Polytechnic University. My main research direction is digital economy and marketing.

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