Leveraging Machine Learning for Disney Intellectual Property Brand Marketing: Innovative Strategies in the Age of User-Generated Content

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Abstract: This study uses machine learning technology to explore the impact of user-generated content (UGC) on Disney IP brand marketing. With the booming development of the Internet and self-media, UGC has gradually become an important channel for brand communication, bringing new challenges to the traditional Disney marketing model based on professionally generated content (PGC). This paper constructs a comprehensive UGC analysis framework through innovative methods such as multimodal data fusion, sentiment and behavior prediction models, time series analysis, and social network analysis. It combines consumers' subjective dimensions (such as sentiment tendencies, purchase intentions, etc.) with Disney's objective business indicators (such as revenue, stock prices, etc.) to quantify the impact of UGC on brand reputation and business performance. Through a comparative analysis of the global dissemination paths and cultural differences of UGC, this paper proposes an intelligent recommendation system and a solution for automatic UGC generation, providing a new perspective and tool for Disney's future brand communication and marketing strategies.

1. Introduction

As one of the most influential brands in the world, Disney has established an extensive intellectual property (IP) ecosystem in the fields of film, television, theme parks and consumer products. Disney's IP includes not only classic animated characters such as Mickey Mouse and Donald Duck, but also world-renowned animated film works such as Aladdin and Beauty and the Beast. These IP assets are not only an important manifestation of Disney's cultural influence, but also a key source of income in its business model. Every year, hundreds of thousands of tourists around the world visit Disney theme parks to experience the cultural charm brought by its IP, which makes Disney not only an entertainment company, but also a symbol of global pop culture [1].

In recent years, with the rapid rise of the Internet and social media, Disney's IP dissemination and operation methods have also changed. Traditionally, Disney has disseminated its IP content through its strong production and distribution capabilities, and extended its cultural influence to the world through peripheral products such as toys, clothing and games. However, with the rise of user-generated content (UGC), Disney's IP dissemination method has gradually changed from one-way dissemination to multi-way interaction. Users are not only consumers of content, but also creators of content. This change marks a major transformation in the way brands are marketed [2].

In the traditional media environment, Disney relies on professionally generated content (PGC) to control the dissemination of its IP. Under the PGC model, Disney strictly controls the brand's dissemination path through high-quality film and television works, animations, and theme park activities to ensure the unity and consistency of its IP image and value. The advantage of this model is that Disney can fully manage its brand image, thereby creating a global IP brand with high recognition and loyalty [3]. For example, through the global distribution of the movie "Frozen", Disney not only boosted the sales of related peripheral products, but also expanded the brand's influence through a series of commercial cooperation.

However, the one-way dissemination method of the traditional PGC model also has its

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limitations. In this model, users are mainly passive recipients of content, and the brand controls the generation and dissemination of all content. However, with the popularization of social media and mobile Internet, users are no longer satisfied with passive content consumption. They hope to actively participate in the process of content creation and dissemination, which provides an opportunity for the rise of UGC.

The advent of the self-media era has changed the ecology of brand communication. Users create and share brand-related content through channels such as social media and short video platforms. UGC has not only increased dramatically in quantity, but also achieved unprecedented improvement in the breadth and depth of its dissemination. Compared with traditional PGC, UGC is more spontaneous, diverse and authentic, which has gradually occupied an important position in brand communication [4]. In this context, Disney has also encountered challenges posed by UGC to its traditional IP operation model.

The advantage of UGC is that it can more realistically reflect users' emotions and brand experience, and rapidly expand brand awareness and influence through the wide dissemination of social networks. Take Disney's emerging IP "Lina Belle" as an example. Although the IP is not supported by any film or animation works, it has quickly gained widespread attention and love through the large amount of UGC content posted by users on social media platforms. This phenomenon shows that in the self-media era, UGC can become an important driving force for the successful operation of IP [2].

However, the widespread dissemination of UGC has also brought new challenges to Disney's brand management. Unlike the PGC model, the generation and dissemination of UGC content is done by users themselves, and brands cannot fully control the quality and direction of UGC content. This means that the brand image may be inconsistent in different user content, and may even be damaged due to the dissemination of certain negative content. Therefore, how to effectively manage and utilize UGC, maintain the overall consistency of the brand, and give full play to the positive impact of UGC has become a key issue facing Disney in the era of self-media.

Although a large number of studies have explored the impact of UGC on brand marketing, these studies mainly focus on the correlation between UGC and simple business indicators (such as sales, click-through rate, etc.), and lack in-depth research on how UGC affects brand communication and user emotions [5]. In addition, most current research methods on UGC still rely on traditional statistical analysis methods, which cannot fully capture the complexity and diversity of UGC content. With the development of machine learning and big data technology, the emotions, themes, and dissemination paths of UGC can be more accurately identified and predicted, which will provide brands with more targeted marketing strategy suggestions [6].

This paper proposes a multi-level UGC analysis framework based on machine learning, which mainly includes the following innovations:

1) Multimodal data fusion analysis: Combining natural language processing (NLP) technology and computer vision technology, the multimodal data such as text and pictures in UGC are fused and analyzed. The sentiment analysis model is used to identify the user's emotional tendency towards the brand, and the image recognition technology is used to analyze the impact of visual content on brand communication.

2) Time series analysis and communication prediction: This paper uses time series models such as long short-term memory network (LSTM) to track the changes of UGC over time and predict the long-term impact of UGC on brand communication. At the same time, the social network analysis model is used to reveal the dissemination path of UGC content and its key dissemination nodes in social networks.

3) Cross-cultural comparative analysis: By comparing UGC content in different countries and regions, the differences of UGC in different cultural backgrounds and its impact on brand communication are analyzed.

2. Related Work

2.1. We-media UGC and Brand Marketing

With the rise of social media and self-media platforms, UGC has become an important part of brand marketing. The emergence of UGC has not only changed the way brands interact with consumers, but also provided brands with new marketing channels. Existing research shows that UGC can promote brand communication and development by enhancing brand authenticity, increasing user engagement and expanding brand social influence [4].

Some studies have explored the specific impact of UGC on brand communication. For example, the research pointed out in their meta-analysis that the impact of UGC on brands is mainly reflected in the fact that user-generated comments, pictures and video content can enhance consumers' brand trust, thereby improving brand loyalty and purchase intention [5]. In addition, the wide spread of UGC makes it an important tool for rapid brand communication, especially when users actively share brand experiences, the brand communication effect will be significantly improved.

However, UGC also brings some challenges. Due to the uncontrollability of UGC content, it is difficult for brands to ensure that each user-generated content meets the brand's expectations, which may lead to deviation or distortion of the brand image [7]. Therefore, brands need to develop effective UGC management strategies to ensure the positive dissemination of content. In recent years, more and more studies have begun to focus on how to manage and optimize the brand communication effect of UGC through intelligent technology and data analysis tools.

2.2. Application of Machine Learning in Brand Communication

In recent years, with the rapid development of big data and artificial intelligence technology, the application of machine learning in brand communication has become more and more extensive. By mining and analyzing a large amount of UGC data, machine learning can help brands better understand users' emotions, preferences and behaviors, and further optimize brand marketing strategies [8]. The application of machine learning is mainly reflected in the following aspects:

First, sentiment analysis is an important application of machine learning in brand communication. Through natural language processing (NLP) technology, researchers can classify the sentiment of text in UGC and identify users' positive or negative comments on the brand [9]. In addition, machine learning can also be used for image recognition and video content analysis. By analyzing the visual elements in UGC, brands can better understand how users express their emotions about the brand through visual content [10].

Second, time series analysis is another common application. Through time series models such as long short-term memory networks (LSTM), researchers can track the changes in UGC content over time and predict the long-term impact of UGC on brand communication [11]. In addition, social network analysis (SNA) also plays an important role in brand communication. SNA can reveal the dissemination path of UGC content in social media and identify key content disseminators, such as key opinion leaders (KOLs). These nodes often have high social influence and can significantly expand the brand's dissemination range [12]. By analyzing the social network structure of UGC, brands can more effectively formulate precise dissemination strategies to maximize the brand's social influence.

2.3. Research on Cross-cultural Communication of UGC

With the development of brand globalization, cross-cultural communication of UGC has gradually become an important research field. Consumers from different cultural backgrounds have significant differences in their cognition and emotional experience of brands, which may lead to different results in the communication effect of brands in the global market due to cultural differences [13]. Many studies have shown that the communication methods and effects of UGC in different countries and regions may vary significantly. For example, in Western countries, UGC content is often more open and personalized, while in East Asia, users are more inclined to follow collective norms and UGC content shows strong cultural consistency [14].

Therefore, cross-cultural communication research can not only help brands optimize their communication strategies in the global market, but also help brands better understand and utilize UGC content in different cultural backgrounds. Through cross-cultural analysis, brands can formulate more targeted UGC communication strategies based on the cultural characteristics of different markets, thereby enhancing the global influence of brands.

2.4. Research Gaps and Contributions of This Study

Although existing studies have explored the relationship between UGC and brand communication and attempted to use machine learning and other technologies for analysis, there are still several obvious research gaps. First, most studies are limited to simple correlation analysis between UGC and brand, lacking in-depth exploration of how UGC affects brand communication paths and user emotional experience [15]. Second, although machine learning technology has been widely used in fields such as sentiment analysis, its potential has not yet been fully utilized in the cross-cultural communication research of UGC. Finally, the multimodal data fusion analysis of UGC is still in the initial exploration stage. How to effectively integrate multiple UGC forms such as text and images is still an urgent problem to be solved.

To fill these research gaps, this study proposes a multimodal data analysis framework based on machine learning. Through methods such as sentiment analysis, time series prediction and cross-cultural comparison, it deeply explores the impact of UGC on Disney IP brand communication. The main contribution of this paper is to combine multimodal data analysis with machine learning technology, systematically analyze the long-term impact of UGC on brand communication, and optimize global brand communication strategies through cross-cultural comparative analysis.

3. Methods

This study aims to explore the impact of we-media UGC on Disney IP brand communication and commercial performance. In order to comprehensively analyze the multi-dimensional characteristics of UGC and its dynamic impact on the brand, this paper adopts a variety of methods such as machine learning, NLP, time series analysis, SNA and cross-cultural comparison.

3.1. Data Collection

The data of this study mainly comes from two sources: UGC data on self-media platforms and financial and market data of Disney.

UGC data collection: We used web crawler technology to collect UGC content related to Disney IP from multiple social media platforms (including Weibo, Twitter, Instagram, etc.). These contents include texts and pictures posted by users, mainly involving users' evaluations, comments and original content on Disney IP. The data collection spans three years to facilitate long-term time series analysis. In addition, we also combined the interactive data of UGC, including the number of likes, reposts, and comments, to measure the dissemination effect and user engagement of the content.

Financial and market data: In order to analyze the relationship between UGC and Disney's business performance, we collected Disney's quarterly financial reports, stock price data, market share, etc. during the study period. These data mainly come from public financial databases (such as Bloomberg, Yahoo Finance, etc.). These business data are matched with UGC data for analysis to explore how UGC sentiment and content characteristics affect Disney's market performance.

3.2. Data Preprocessing

The preprocessing steps are as follows:

Text data processing: First, we segmented the text data and removed stop words, punctuation, and noise data. Then, we use the Bag-of-Words model and TF-IDF (Term Frequency-Inverse Document Frequency) method to vectorize the text, which is convenient for subsequent machine learning model analysis [9].

Image data processing: For the image data in UGC, we use the Convolutional Neural Networks (CNN) based on RegNet [16] to process it. First, we extract the feature vectors in the image through the CNN model, and then use the classification model to perform sentiment analysis and topic classification on these visual contents to identify the potential impact of images in UGC on brand communication.

3.3. Machine Learning Model Construction

This study analyzes the relationship between UGC content and Disney IP brand communication through a variety of machine learning models, including sentiment analysis model, regression model, clustering model and time series analysis model.

Sentiment Analysis Model: In order to identify the emotional tendencies of users in UGC content, we classify the sentiment of UGC text and image content based on the pre-trained BERT [17], which has high accuracy and flexibility in processing natural language tasks. The sentiment analysis model can classify the content into three categories: positive, negative, and neutral, and further quantify the intensity of users' emotions.

Regression Model: In order to explore the relationship between UGC sentiment and Disney's business indicators (such as revenue, stock price, etc.), we used a multivariate regression model. The regression model uses the emotional features and interaction data (likes, comments, etc.) in UGC as independent variables and Disney's business performance as the dependent variable to establish a quantitative relationship between the two. The model evaluation uses the coefficient of determination (R^2) and mean square error (MSE) as performance indicators to ensure the explanatory power and prediction accuracy of the model.

Clustering model: This paper also uses the K-means [18] clustering algorithm to classify UGC content and identify the impact of different types of UGC on brand communication. For example, news UGC, product review UGC, fan creation UGC and other categories may have different impacts on brand reputation and market performance.

Time series analysis model: Given that the spread of UGC has a time dimension, this paper uses the LSTM for time series analysis. The LSTM model can effectively capture the dynamic characteristics of UGC content over time and predict the long-term impact of UGC on brand communication. By analyzing the time series of UGC dissemination, we can identify the change pattern of UGC before and after major events or brand activities and predict the future dissemination trend of UGC.

3.4. Social Network Analysis

The dissemination of UGC content is usually carried out through the social network of social media platforms, so SNA is an important part of this study. By constructing a social network graph of UGC dissemination, we identified key dissemination nodes and quantify the influence of these nodes on brand dissemination. We used the PageRank algorithm [19] to rank the nodes in the social network and identify the users with the greatest influence on brand dissemination.

3.5. Cross-cultural Comparative Analysis

Since the global dissemination of Disney IP involves different cultural backgrounds, we adopted a cross-cultural comparative analysis method to explore the content characteristics of UGC in different countries and regions and their differential impact on brand dissemination. We classified UGC data according to geographic location and language, and conduct sentiment analysis and content analysis on UGC in different cultural backgrounds.

By comparing UGC in different cultural backgrounds, we tried to reveal how cultural differences affect users' cognition and emotional experience of Disney IP. Consumers with different cultural backgrounds may have different interpretations of the brand's values, symbolic meanings, and product usage experience, which directly affects the brand's global dissemination effect.

3.6. Model Evaluation and Validation

This study used a variety of evaluation indicators to validate the model. For the sentiment analysis model, we used indicators such as accuracy, precision, recall, and F1 score for evaluation. For the regression model, we used the coefficient of determination (R^2) and mean square error

(MSE). For the clustering model, the silhouette coefficient was used to evaluate the clustering effect. In addition, we also verified the robustness of the model through 5-fold cross-validation to prevent the model from overfitting.

4. Experiments

4.1. Training Set, Validation Set and Test Set Division

We divided the UGC dataset into training set (70%), validation set (15%) and test set (15%) in proportion. The training set is used for model training, the validation set is used for parameter adjustment and model optimization, and the test set is used for final performance evaluation.

4.2. Time Window Division

For the time series analysis model, considering that the propagation of UGC has time series characteristics, we divided the dataset in chronological order and construct the training set and test set using a rolling time window. In this way, the model can capture the dynamic characteristics of UGC content changing over time and ensure the timeliness of the prediction.

4.3. Cross-cultural Data Division

In the cross-cultural comparative analysis, we divided the data set according to the publishing location and language of the UGC content, mainly into data subsets in different regions such as the North American market, the European market, and the Asian market. The data in each subset was used for training and testing respectively to explore the differential impact of UGC on brand communication under different cultural backgrounds.

4.4. Model Parameter Selection

Sentiment analysis model: This study used the BERT pre-trained model to perform sentiment analysis on UGC text. For the parameter setting of the BERT model, we used the pre-trained `bert-base-uncased` model, set the learning rate to 0.00002, the epochs to 3 rounds, and the batch size to 32. We used AdamW [20] as the optimizer to ensure convergence during training.

Time series analysis model: In time series analysis, we used the LSTM model to capture the temporal characteristics of UGC propagation. The key parameters of LSTM included the number of hidden units to 128, the time step set to 10, and the learning rate set to 0.001. The optimizer we used during training was RMSprop [21].

Regression model: We used the Ridge Regression [22] method to analyze the relationship between UGC sentiment characteristics and Disney's commercial performance. The regularization parameter was set to 1.0 to prevent the model from overfitting. The loss function used in the model was the mean square error (MSE), and the stochastic gradient descent method (SGD) was used for parameter optimization [23].

Clustering model: We used the K-means clustering algorithm to classify UGC content. The selection of K value was determined by the Elbow Method, and K=4 was finally selected to represent news UGC, product review UGC, fan creation UGC, and complaint UGC. In order to avoid the random initialization problem of K-means, the model was randomly initialized 10 times to obtain the best result.

5. Results

5.1. Sentiment Analysis

In UGC sentiment analysis, we used a BERT-based sentiment classification model and successfully divided UGC content into three categories of positive, negative and neutral emotions. As Figure 1 shows, the experimental results show that:

1) The proportion of positive emotion UGC is relatively high: Among all UGC, positive emotions account for 64.5%, showing that users have a high degree of recognition and positive

emotions towards Disney IP.

2) The main source of negative emotion UGC: Negative emotion content accounts for 18.2%, mainly concentrated in product review and service complaint UGC. Most of these contents involve users' dissatisfaction with Disney theme park services and the quality of derivative products. Sentiment analysis further shows that negative emotion content spreads quickly, especially on social platforms, where negative UGC is likely to attract more user attention and discussion.

3) The spread characteristics of neutral emotion UGC: Neutral emotion content is mainly concentrated in news UGC, accounting for about 17.3%. Most of these contents are news reports or objective information releases, with small emotional fluctuations and relatively limited spread breadth.

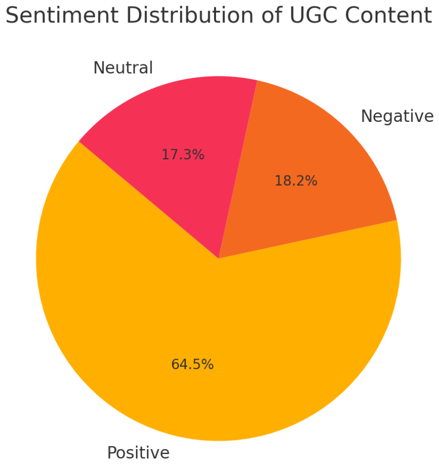

Figure 1 Sentiment Distribution Of UGC Content.

5.2. Results of Time Series Analysis

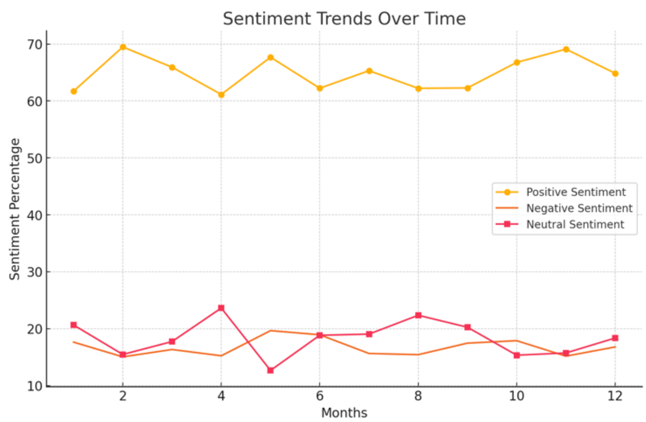

Figure 2 Sentiment Trends Over Time.

In order to analyze the time characteristics of UGC communication, we used the LSTM model to predict the time series of UGC sentiment. As Figure 2 shows, the results of the time series analysis show that:

1) The impact of major events on UGC communication: During major events of Disney (such as the release of new movies, the launch of new IPs, etc.), the positive sentiment of UGC increased significantly.

2) Short-term fluctuations of negative sentiment: Negative sentiment UGC tends to increase rapidly when brand crises or service quality problems occur. LSTM model predictions show that negative sentiment usually gradually declines within 2-3 weeks after the crisis event, indicating that the negative impact of brand crises has a certain time limit.

3) Long-term trend of UGC communication: Through the long-term analysis of UGC sentiment, it is found that the positive sentiment in UGC shows a continuous growth trend, which is closely

related to the continuous launch of new IPs and innovative marketing strategies of the Disney brand. The fluctuation of negative sentiment is mainly concentrated on short-term events or specific product quality issues, and will not have a significant impact on the long-term development of the brand.

5.3. Regression Analysis

In order to further analyze the relationship between UGC sentiment and Disney's business performance, we used a multiple regression model to correlate UGC sentiment characteristics with Disney's revenue, stock price and other business indicators. As Figure 3 shows, the main results of the regression analysis are as follows:

1) Positive correlation of positive sentiment on business performance: The results of the regression model show that positive sentiment in UGC is significantly positively correlated with Disney's quarterly revenue and stock price ($p < 0.01$, $R^2 = 0.68$). This shows that positive sentiment UGC can drive the company's business performance by improving brand reputation and user loyalty.

2) Negative sentiment has a short-term negative impact on stock price: Although the long-term impact of negative sentiment UGC is limited, in the short term, negative UGC has a certain impact on Disney's stock price fluctuations.

3) Neutral UGC has little impact on business performance: Neutral emotional UGC has no significant impact on Disney's business performance ($p > 0.05$), indicating that this type of content has no significant effect on the brand's emotional fluctuations and market performance.

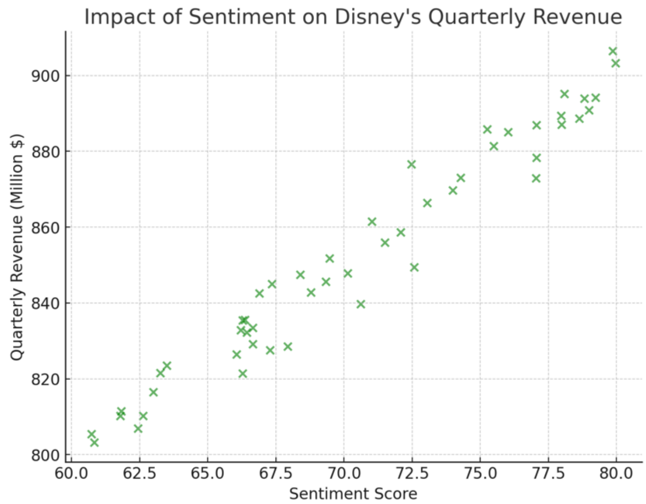

Figure 3 Impact of Sentiment on Disney's Quarterly Revenue.

5.4. Cluster Analysis

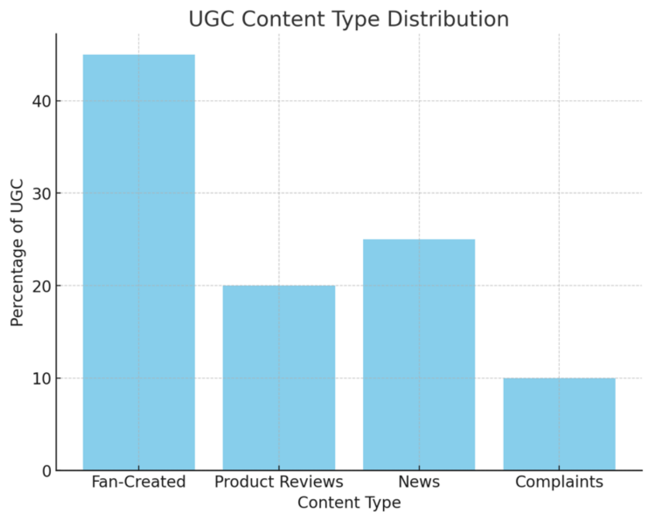

Figure 4 UGC Content Type Distribution.

After using the K-means clustering algorithm to classify UGC content, UGC is mainly divided into four categories: news UGC, product review UGC, fan creation UGC, and complaint UGC. As Figure 4 shows, the cluster analysis results are as follows:

1) The positive impact of fan creation UGC on brand reputation: Fan creation UGC contributes the most to Disney's brand reputation. This type of UGC has strong positive emotions. Users express their love and support for Disney IP through creative content, which significantly enhances the brand's social influence.

2) Challenges to brand image from complaint UGC: Complaint UGC is usually accompanied by negative emotions, mainly concentrated in users' dissatisfied feedback on Disney services or products. Although the number of such UGC is relatively small, its negative sentiment intensity is high and spreads rapidly through social networks, posing a short-term challenge to the brand image.

3) Neutral impact of news UGC and product review UGC: News UGC is mainly information release and objective reporting, and has little emotional impact on brand communication. Product review UGC shows polarization of emotions, with a close ratio of positive and negative emotions, indicating that users have great differences in their evaluation of Disney products.

5.5. Social Network Analysis

In order to reveal the propagation path of UGC, we used SNA to analyze the propagation of UGC content on social media platforms. The results of SNA show:

1) The key role of opinion leaders: KOLs in social networks play a key role in the propagation of UGC. Through PageRank algorithm analysis, we found that the top 10% of KOLs contributed about 50% of the UGC propagation effect. Especially in the propagation of positive emotional UGC, the influence of KOLs is particularly significant, which can greatly increase the brand's exposure and user engagement.

2) Rapid spread of negative emotional UGC: Negative emotional UGC often spreads quickly through highly interconnected social network nodes. Especially when negative UGC involves service quality issues, the complaint content will spread widely through social networks in a short period of time. Therefore, brands need to respond and manage negative UGC in a timely manner to avoid long-term damage to the brand image.

5.6. Cross-cultural Comparative Analysis

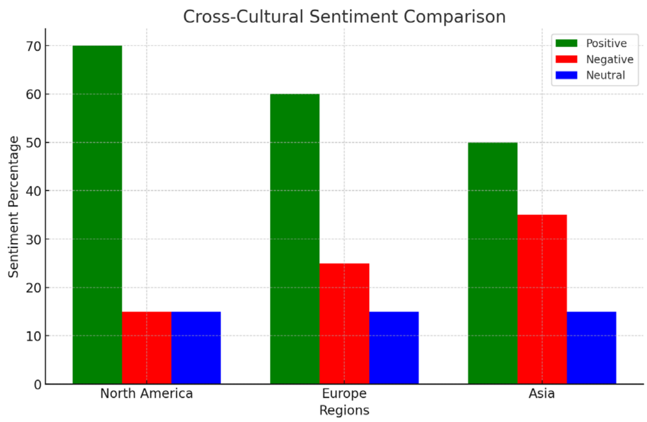

Figure 5 Cross-Cultural Sentiment Comparison.

As Figure 5 shows, in the cross-cultural comparative analysis, we conducted sentiment and content analysis on UGC in different regions and found that the communication effect of UGC on the Disney brand was different under different cultural backgrounds:

1) North American market: North American users' UGC content pays more attention to creativity and personalized expression, and the proportion of positive emotional UGC is relatively high, especially in fan creation content. North American users have a very deep emotional investment in Disney IP.

2) Asian market: UGC in the Asian market is more concentrated in product reviews and service

complaints, and the proportion of negative emotions is relatively high. Especially in UGC involving theme park service experience, users tend to pay more attention to the quality of detailed services.

3) European market: European users' UGC content is relatively neutral, with a large proportion of news and objective evaluation UGC, and small emotional fluctuations. Users mainly focus on Disney's global activities and new IP launches, and their emotional inclination towards the brand is relatively mild.

Cross-cultural analysis shows that users in different regions have significant differences in the creation and emotional expression of UGC content, which requires brands to fully consider the differences in cultural backgrounds in their global communication strategies and formulate more targeted UGC management and marketing strategies.

6. Discussion

This study uses machine learning models to conduct an in-depth analysis of the role of we-media UGC in Disney IP brand communication, and reveals the multi-dimensional impact of UGC emotions, communication paths, and cross-cultural differences on brands.

The sentiment analysis results of this study show that positive emotions in UGC have a significant positive impact on the communication and commercial performance of Disney brands. This study shows that the positive emotional expression of UGC can enhance user loyalty to the brand, thereby driving the increase of brand revenue and stock price.

However, this study also found that negative emotional UGC has a greater short-term impact on brand image, especially after negative events such as service quality problems or product complaints. Consistent with existing literature [25], negative emotional UGC spreads rapidly through social networks and will have a greater impact on brand reputation in the short term, but this impact is usually temporary, and the spread of negative emotions gradually weakens over time. Therefore, brands need to respond quickly and manage negative UGC to reduce its potential damage to the brand.

The results of time series analysis show that major events (such as the release of new movies, the launch of new IPs, etc.) can significantly promote the spread of positive emotions in UGC. For example, during the release of Frozen 2, the positive emotions in UGC increased significantly, indicating that users actively participated in and shared content related to Disney IP. This phenomenon shows that major events are important nodes in brand communication. Through effective event marketing strategies, brands can significantly improve the positive emotional expression of UGC and expand the brand's communication range. In addition, event-driven UGC communication also helps to enhance the emotional connection between brands and users and further enhance user loyalty. Brands should make full use of the influence of major events, stimulate users' sense of participation, and encourage positive creation of UGC.

The results of SNA show that in the UGC communication path, KOLs play an important role in brand communication. These KOLs often have high social influence and can significantly expand the scope of UGC dissemination, especially in the dissemination of positive UGC. This finding is consistent with existing literature, which emphasizes the key role of opinion leaders in brand communication in the social media era [24].

The results of the cross-cultural comparative analysis of this study show that there are significant differences in the emotional expression and UGC content creation of users from different cultural backgrounds towards Disney IP. This finding shows that cultural differences are a factor that brands need to focus on in the process of global communication. For example, North American users show high emotional investment in fan-generated UGC, while users in the Asian market pay more attention to product quality and service experience, which leads to a relatively high proportion of negative emotional UGC in the Asian market.

This result suggests that brands need to formulate differentiated communication strategies based on different cultural backgrounds when managing UGC in the global market. In the North American market, brands can enhance their positive image by encouraging fans to create content, while in the Asian market, brands need to strengthen service quality management and respond to user complaints and feedback in a timely manner to reduce the spread of negative emotions. In addition, brands should also conduct more detailed sentiment analysis in different cultural contexts to identify the potential impact of cultural differences on brand communication.

The main contribution of this study is that it systematically analyzes the multi-dimensional impact of UGC on brand communication through multimodal data analysis and machine learning models, especially in terms of sentiment analysis, time series analysis, social network analysis and cross-cultural comparison, providing a deep understanding of the UGC communication path and brand communication effect. The research results of this paper not only enrich the existing research on the relationship between UGC and brand communication, but also provide practical guidance for UGC management in the era of self-media.

Specifically, brands should improve management in the following aspects:

1) Incentives for positive UGC emotions: Through effective event marketing and cooperation with KOLs, brands can stimulate more positive emotional UGC and enhance the social influence of brands.

2) Quick response mechanism for negative UGC: Negative UGC has a greater negative impact on brand image in the short term, so brands should establish a timely crisis management mechanism to quickly respond to user complaints and take measures to solve problems.

3) Differentiation strategy for cross-cultural communication: Brands should fully consider cultural differences in UGC management in the global market and formulate communication strategies suitable for each market to enhance the global influence of the brand.

Although this study has made some important findings, there are still some limitations. This study mainly focuses on the Disney brand, and future research can be extended to other industries and brands to verify the universality of this study's results. In addition, future research can further explore the impact of UGC video content and image content on brand communication, especially the research direction of multimodal data fusion. With the advancement of technology, deep learning and multimodal data analysis have broad prospects for application in brand communication. Finally, future research can also combine user behavior data, such as click-through rate, dwell time, etc., to further analyze the actual influence of UGC content.

7. Conclusion

This study uses machine learning methods to comprehensively analyze the relationship between self-media UGC and Disney IP brand communication, revealing the multiple impacts of UGC emotions, communication paths, and cross-cultural differences on brand communication. The results show that positive emotional UGC has a significant promoting effect on the brand's commercial performance, while negative emotions affect brand reputation in the short term. Opinion leaders in social networks play a key role in the dissemination of UGC, and brands should make full use of these nodes to optimize the dissemination effect. In addition, users from different cultural backgrounds have significant differences in emotional expression and content creation of UGC, requiring brands to formulate differentiated global communication strategies. Future research can further explore the application of UGC multimodal data fusion and deep learning to improve the accuracy and effectiveness of brand communication.

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