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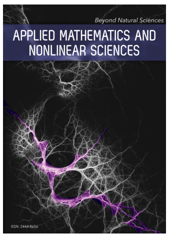

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On the improvement, innovation and inheritance of stage makeup styling in opera under the background of big data

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Abstract

Character styling design can clearly show the background of story characters and the characteristics of the times in the performance of stage plays. Integrating traditional culture with the art of stage plays is important for developing theatrical communication. In this paper, we analyze the factors that impact theatrical communication in the context of big data. Based on the original innovation diffusion model, it analyzes the limitations of its application, analyzes the innovation characteristics of theatrical stage makeup modeling from a qualitative perspective, finds that its diffusion characteristics do not conform to the prerequisite assumptions of the original innovation diffusion model, and confirms the improvement direction of the innovation diffusion model. Based on the analysis of audience data by the full data analysis method, the main influencing factors affecting the diffusion of opera heritage are identified, and their practical significance in the improved model is analyzed. The original innovation diffusion model is improved quantitatively, and an iterative diffusion model is established. Empirical analysis of the iterative diffusion model was conducted using the actual diffusion data of opera stage makeup styling. The research results show that the initial diffusion rates of the products are, in descending order, Cheese Superman, TikTok, Watermelon Video, and Punchbowl. Among them, the cumulative diffusion of TikTok is the highest at 14, and the diffusion rate of Watermelon Video is 0.68. It indicates that the above products effectively spread opera culture and highlight the charm of opera stage makeup styling.

Keywords: Big data background; On opera stage; Makeup modeling; Innovation diffusion model; Iterative diffusion model
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1 Introduction

In the present time of rapid development of information technology, the emergence of smart TVs, and the development of Internet technology, the ways for people to disseminate and receive information are increasing, the interaction between communicators and recipients are becoming more frequent, and the data generated is growing rapidly at a geometric rate [1-3]. In the case of theater, for example, communication between actors and audiences and between audiences is no longer limited to the theater on and off stage but can be done directly through Internet technologies: microblogging, WeChat, etc. [4]. Huge amounts of data are stored by web servers and are used by people to solve various complex problems after being organized and analyzed by big data, and theatrical communication is among them [5]. Therefore, using big data to analyze and study current theatrical communication may provide new ideas and open up new paths for the future development of theater [6].

Opera is an artistic treasure of the Chinese nation, gathering the research and dedication of old artists who have worked hard for generations to advance human progress [7]. From ancient times to the present, artists have invented a variety of classic opera arts, leaving us with many precious treasures [8]. Opera interprets human life, simulates time and space, and presents a comprehensive picture of the normal way of life of the Chinese nation and our expectations, expectations, and goals in life, forming a moving and Chinese graphic history [9-11]. Opera summarizes various art forms such as literature, fine arts, martial arts, and acrobatics, and character modeling in opera plays a very important artistic effect in performance for this audiovisual art [12-14]. In contemporary stage productions, artists have explored everything from the script's content to the performance style, from the core concept of opera to the characteristics of the performance art, from the shape of the stage to the viewing of the performance [15-17]. The current stage art has slowly changed from a wide range of props to show the realism of life to a three-dimensional sense of space on the stage with an emphasis on writing to express the mood while showing the coexistence of reality and mood and a variety of styles and forms of scenery [18-21]. In the current digital information era, some traditional culture, such as opera culture, has been gradually replaced by online culture, and our young people are gradually unfamiliar with opera, so how to integrate this ancient traditional culture with the more active stage art now and to have a new understanding of traditional culture and pass it on is an urgent task now [22-25].

The literature [26] considers folk music as a heavy cultural carrier. It still has a unique charm and appeal in today’s flourishing culture. The intangible heritage of folk music needs to be continued and passed on by modern Chinese so that its spirit and distinctive culture can be successfully transformed into educational achievements. To this end, it would be feasible to promote and inherit folk music from the perspective of intangible cultural heritage, using shuyuan education as the central vehicle. Combining the understanding of intangible cultural heritage and the thinking of promoting and inheriting folk music from the perspective of intangible cultural heritage, the article further discusses the meaning and strategy of promoting and inheriting folk music centering on vocal music teaching in colleges and universities, hoping to provide valuable references for related researches. The literature [27] argues that stage language differs greatly from normal conversational language in duration, loudness, and pitch. These characteristics of stage language and conversational language were compared. Method A well-known and experienced female singer reads the same lyrics on stage and in a conversational speech. Significant differences were found. The results were longer word and sentence durations and less variation in word durations for stage speech compared to conversational speech. The average sound level was 16 dB higher. At the same time, the average fundamental frequency was also much higher and more variable.

In sentences, both loudness and fundamental frequency tended to follow a low-high-low pattern of variation. Some findings fail to support the current view on the characteristics of stage speech in the sense that this study shows the relevance of objective measurements in describing vocal style. The main aim of the literature [28] is to codify conservation policies and identify types of actions for the main archaeological sites of tourism value in Greece in order to define a spatial planning framework to address the challenges of reducing the impact of climate change, such as: adopting an integrated design approach for the conservation of cultural heritage, instead of traditional conservation methods, linking cultural heritage to the natural environment, bridging existing gaps, redefining dynamically and spatially cultural heritage to adapt to climate change and also for emergency preparedness and disaster risk reduction. The literature [29] aims to explore the development of 360° virtual tours of traditional Malay houses over 100 years old as one of the important measures to preserve, protect and interpret the architectural heritage and cultural history. The primary data were analyzed through high-resolution photography using a fisheye lens digital camera to analyze the architectural inventory. The collected photos were combined with stitching techniques to create a panoramic effect. 360° virtual tour application was developed based on multimedia development life cycle theory. The study results show that the application was produced as a digital database containing data on qualitative physical attributes managed and recorded by the university for posterity. The results of this study demonstrate how technology can transform traditional learning and museum tours into an enjoyable learning platform that motivates and understands architectural structures and unique architectural details. The literature [30] aims to explain the infrastructural challenges of Malay Kampung as a cultural heritage area. The research methodology employed was qualitative and included field observations and secondary data collection. Interviews were conducted to clarify the field data and the condition of the remaining historic buildings. Based on the results of the field observations, secondary data were obtained for planning infrastructure improvements in Dadapsari village, where Malay Kampung is included in the management of the village. The study results show that there is still a physical decline in the settlement and environment, with tidal flooding, damaged roads and drainage systems, habitable houses, and a lack of open space. The physical decline has also occurred in several old buildings with a long history, which remain unappreciated in this development. The revitalization of the old Semarang area through infrastructure development must still be considered a cultural heritage area. In particular, the restoration and reconstruction of decaying cultural heritage buildings is a priority.

It is significant to inherit and innovate the design method of theatrical stage makeup styling. For this reason, this paper proposes a thesis on the improvement, innovation, and inheritance of theatrical stage makeup styling in the context of big data. Firstly, in the context of big data, more accurate results can be obtained, and theatrical communication will apply the data indicators of audience feedback to every aspect of communication so that the effect of theatrical communication can be continued. Based on the original innovation diffusion model for improvement, an iterative product diffusion model applicable to the innovation of stage makeup styling in opera was constructed, and the actual product diffusion data were used for empirical analysis to determine the three main influencing factors affecting product diffusion and their practical significance in the improved model. Then, the model improvement principle was determined for the characteristics of opera heritage diffusion. Second, based on the improved product iterative diffusion model, the evolutionary features of the life cycle of opera stage heritage are explored through four product case studies.

2 Drama communication in the context of big data

Big data in drama communication mainly comes from audience data, which can reflect the communication effect of drama. The application of the full data analysis method in theater communication focuses on the collection, organization, and analysis of audience data and the deep mining of effective audience information in the huge and complicated audience data by establishing data models and performing data calculations [31]. The effect of theater communication is affected by many factors: the quality of the script, the actor's performance, the stage's design, the use of marketing tools, and the audience's acceptance. Nevertheless, the receptor of communication is mainly the audience. Through the audience's acceptance and feedback of the drama, we can accurately and effectively grasp the drama's direction and enhance the drama's effect. Therefore, in selecting research objects, the focus should be on the audience of drama communication.

The source of big data relies mainly on the Internet, which means that people use various mobile terminals such as computers, cell phones, and tablets to chat on the Internet, send friends, browse various websites and forums, and click on links to various videos, all of which become data to be retained on servers [32]. The sources of audience data for drama communication are similar in this way. Specifically, audience data sources are theater performances, online communication, and television platforms. The huge amount of audience data is the basis for applying the full data analysis method in theatrical communication, and the full data analysis method has an impact on the effect of theatrical communication by sifting through these audience data and stripping out the theatrical-related audience data for collation and analysis.

According to the analysis of audience data by full data analysis method, combined with the research and the opinions of relevant data experts, after screening, finally set 5 audience feedback indicators to analyze the influence factors of drama communication. These 5 indicators are shown in Table 1. In the latter part of the paper, the use of X1, X2, X3, X4, X5 all refer to the audience indicators.

Table 1. Influencing factors of drama communication

Number	Audience metrics	Specific meaning
X1	Attention	Level of interest in theatrical performances
X2	Credibility	Visibility of directors and actors
X3	Activity	Whether you have the habit of going out to activities
X4	Viewing habits	Dependence on media
X5	Preference type	Type of drama

Through the 5 indicators of audience feedback and the change of the sample mean, the following conclusions can be drawn: the higher the value of X1, the greater the audience's attention to drama, and the corresponding value of X2 will also be improved. The value of X3 reflects the active degree of the audience. The higher the value means that the audience is more willing to go into the theater to appreciate drama. The lower the value, the audience prefers to appreciate drama through television or the Internet. At the same time, X4 will also fluctuate under the influence of X3, representing the audience's wish to enjoy and understand the drama in more ways, and X5 indicates the audience's preferred type of drama at a certain stage, the higher the value, the more concentrated the type, the lower the value, the more dispersed the type, and the data model is thus generated. The higher the value, the more concentrated the genre is; the lower the value, the more fragmented the genre is, and the data model is thus generated. After that, it is only necessary to overlay and add on the data samples to immediately see the changes in the values, and by increasing or decreasing the values, it is clear which indicator has a greater impact on the effect of drama communication and which medium is more suitable for the dissemination and development of drama. Therefore, based on the analysis of audience data by the full data analysis method, the data is established by arithmetic to derive various types of audience indicators that affect theater communication.

3 Innovation diffusion theory and model construction

3.1 Overview of Bass model

Innovation diffusion theory is a theory used to explain how new things, such as new opera images and new technologies, spread and diffuse within a social system, mainly based on communication theory. The initial focus of innovation diffusion theory is on communication channels and social systems. With the in-depth research and wide application of the theory, innovation diffusion theory is gradually applied to the fields of technology forecasting and marketing, which makes the research deepen and the focus of research turns to technology forecasting and diffusion models in marketing, intending to predict the future diffusion of new things, to help companies develop marketing strategies and decision support.

By constructing a diffusion model to control many influencing factors involved in the diffusion process, the aim is to accurately predict the future diffusion of new things by controlling the variables that have a regularity in the diffusion process. The diffusion model is constructed by setting a small number of coefficients to form a sales cycle curve for opera images, which provides decision support for predicting future sales of opera images and formulating marketing strategies.

Based on innovation diffusion theory, Western scholars have established several diffusion models to study further the diffusion process of new technologies and new opera images and make predictions, among which the Bass model is the diffusion model of seminal significance. Bass, in his diffusion study of 11 durable goods, proposed a diffusion model that integrates external and internal influences under the premise of setting a series of assumptions. The model assumes that mass media and oral communication influence the diffusion rate of new opera images. Mass media mainly disseminates the attributes of opera image that can be easily verified, such as opera image function and price, while oral communication disseminates the performance of opera image that is difficult to verify, such as opera image reliability and durability. Adopters influenced by mass media are innovators, while adopters influenced by oral communication are imitators. The decision of innovators to adopt or not to adopt a new opera image is not influenced by other members of the social system, while other members influence the decision of imitators to adopt a new opera image in the social system, and the influence increases with the number of adopters.

Fourt and Woodlock proposed the innovator diffusion model, which defines that the innovation behavior of potential adopters determines innovator diffusion, and this model only considers the behavior of innovators influenced by mass media to become adopters, also known as the external influence model. Namely:

$$n(t) = p\left[M - N(t)\right] \tag{1}$$

A model of imitator diffusion is proposed by fully considering the verbal transmission among potential adopters:

$$n(t) = \frac{q}{M} N(t)\left[M - N(t)\right] \tag{2}$$

In equations (1) and (2), M is the maximum market potential of opera image. $n(t)$ is the number of new adopters at time t, $N(t)$ is the cumulative number of adopters at time t, and p is the innovation factor, i.e., the probability that potential adopters are influenced by mass media and become adopters. q is the imitation factor, i.e., the probability that potential adopters are influenced by oral communication and become adopters.

The Bass model defines that opera image diffusion consists of both innovators and imitators. The diffusion rate of the former is influenced by mass media and focuses on easily verifiable opera image attributes, such as opera image function and price. The diffusion speed of the latter is influenced by oral communication and mainly focuses on opera image properties that are difficult to be verified, such as opera image reliability and durability. Its model expression formula is shown in Equation (3).

$$n(t)=\left[p+\frac{q}{M}N(t)\right]\left[M-N(t)\right] \tag{3}$$

The core idea of the Bass model is that at moment t, the proportion of non-adopters who adopt the new opera image is linearly related to the proportion of adopters, and the expression formula is as follows:

$$\frac{f(t)}{\left[1-F(t)\right]}=p+qF(t) \tag{4}$$

Where, $F(t)$ denotes the cumulative adoption rate of the opera image at the moment t, $f(t)$ is a density function of $F(t)$, referring to the adoption rate at the moment, $F(t)=\int_0^t f(t)dt$. Therefore, it can be introduced that the cumulative number of adopters at the moment t, $N(t)=F(t)M$, the number of new adopters $n(t)=f(t)M$, and $qF(t)$ indicates that when the percentage of the adopted number is larger, the stronger the influence on imitators to perform imitation behavior.

The derivative of the above equation is obtained:

$$F(t)=\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{5}$$

$$f(t)=\frac{p(p+q)^2-e^{-(p+q)t}}{\left[p+qe^{-(p+q)t}\right]^2} \tag{6}$$

The Bass model, like all mathematical models, has a set of assumptions as preconditions:

1) The market potential remains constant over the life cycle.

2) The diffusion process is not influenced by competition from other opera images, and the competitive environment is oligopolistic.

3) The process of opera image diffusion is not affected by marketing or operation strategies.

4) The performance of its opera image remains unchanged during its life cycle, and no innovation of opera image is carried out.

5) The territorial boundaries of the social system remain unchanged during the diffusion process.

6) There is no supply constraint in the diffusion process.

7) There are only two stages of user decisions in the diffusion process: adoption and non-adoption.

8) The innovation and imitation coefficients of potential adopters are the same, and there is no difference between users.

The Bass model is the seminal diffusion model, and subsequent studies related to the innovation diffusion model can be broadly divided into two categories: empirical studies on the innovation diffusion model; and model extensions and improvements based on the original innovation diffusion model by relaxing the preconditions.

3.2 Norton model overview

An important premise of the Bass model assumes that the performance of the opera image remains the same during its life cycle and that no innovation will occur. However, in practice, opera image manufacturers tend to innovate and improve the performance of opera images in order to gain a larger market share. Based on this phenomenon, Norton and Bass take DRAM opera image renewal diffusion as an example and study the diffusion curves of different generational versions of opera images, and propose a generational opera image diffusion model, also known as Norton's model, based on the substitution relationship existing between generational opera images.

Norton's model suggests that the market potential for a new opera image of a new generation consists of two components: one is the new market expanded by the improved performance of the opera image or the innovation of the opera image. The other part is the market transferred from the previous generation of opera images, including potential adopters of the previous generation of opera images changing their minds to become adopters of the new opera images, and adopters of the previous generation of opera images switching to adopt the new opera images.

Its Norton model is given below as an example of the coexistence of three generations of opera images.

$$N_1(t)=F(t)M_1-F(t-\tau_2)F(t)M_1=F(t)M_1\left[1-F(t-\tau_2)\right] \tag{7}$$

$$N_2(t)=F(t-\tau_2)\left[M_2+F(t)M_1\right]\left[1-F(t-\tau_3)\right] \tag{8}$$

$$N_3(t)=F(t-\tau_3)\left\{M_3+F(t-\tau_2)\left[M_2+F(t)M_1\right]\right\} \tag{9}$$

where $N_i(t)$ denotes the cumulative proliferation quantity of the ird generation opera image at t time, $F(t)$ denotes the cumulative proliferation quantity of the opera image at t time as a proportion of the total potential market, i.e., the cumulative proliferation rate. M_i denotes the market potential of the ith generation opera image, τ_i denotes the time when the ith generation opera image enters the market, when $t\le\tau_i, F(t-\tau_i)=0$. In the model, $F(t-\tau_2)F(t)M_1$ denotes the number of the 1st generation opera image replaced by the 2nd generation opera image, from which we can see the substitution relationship between multiple generations of opera images.

Norton's model is mostly applied to studying the diffusion of durable goods, such as cell phones, computers, drugs, etc. Norton and Bass empirically analyzed their model using data on the diffusion of high-tech electronic opera images, and the study showed that the cumulative diffusion quantity curve of three generations of opera images is shown in Figure 1.

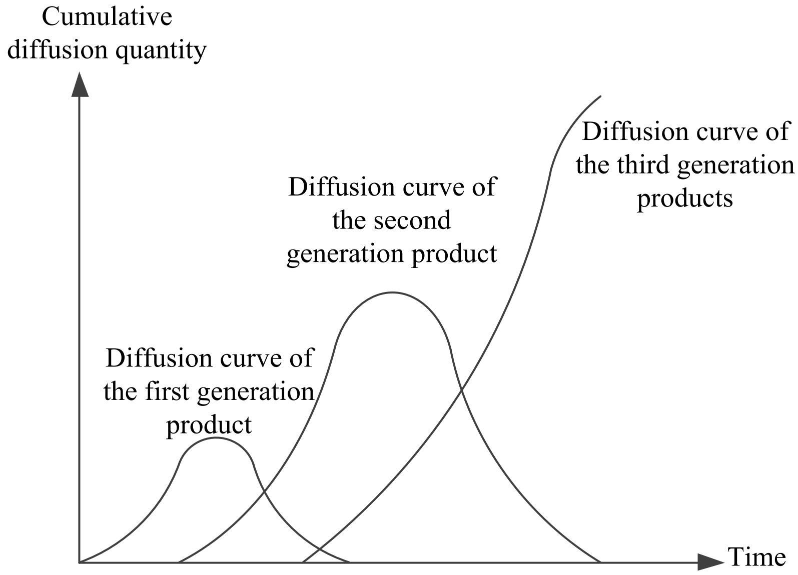


Figure 1. Cumulative diffusion curve of the image of replacement opera

This paper mainly applies the Bass model and Norton model framework to improve the original model based on the special characteristics of opera stage makeup modeling and extend the original model to make it have a broader scope of application and stronger explanatory power.

3.3 Model evaluation indicators

This paper will use the actual diffusion data of the opera stage to conduct an empirical analysis of the innovation diffusion improvement model constructed based on the characteristics of opera stage makeup modeling, i.e., the iterative diffusion model of opera image. Uniform indicators are adopted to evaluate the improvement model to measure the fitting effect and prediction effect of the opera image iterative diffusion model constructed based on the characteristics of opera stage makeup styling on the actual data and to judge whether the improvement model is successful. Integrating the research content and research process of this paper, the improved model will be evaluated from the following two aspects:

On the one hand, it is the fitting effect of the improved iterative diffusion model of opera images. This part is considered from the improved model as a whole, the overall construction effect of the improved model is analyzed, and the degree of fitting of the improved model to the actual diffusion data of opera images is used as the evaluation index. Traditional tests such as t-test and F-test are often adopted in statistics for parameter testing of general linear regression models, but for parameter testing of nonlinear regression models, the parameter testing methods applicable to linear regression models are not available. In this paper, the overall fitting effect of the model is analyzed, and the goodness-of-fit is used as the evaluation index of the model. The goodness-of-fit statistic is the coefficient of determination R2, the degree of fit of the regression model to the observed values. Its expression form is as follows:

$$R^2 = 1 - \frac{\sum (y - \hat{y})^2}{\sum (y - \bar{y})^2} \tag{10}$$

y represents the actual value, $\hat{y}$ represents the estimated value obtained from the constructed regression model with the same independent variable, and $\bar{y}$ represents the sample mean. The value of goodness-of-fit R^2 ranges from (0, 1), and when the value of goodness-of-fit R^2 is larger and closer to 1, it means that the regression model fits the observations better, and vice versa, it means that the regression model fits the observations worse.

The other side is the prediction effect of the improved iterative diffusion model of opera images. In this section, the predicted and actual values of the improved model for the future diffusion of opera images are compared and analyzed, and the relative error and the results of the parametric test of whether there is a significant difference between the predicted and actual values are used as evaluation indicators. The relative error between the predicted and actual values of the improved model is calculated, and the prediction effect of the improved model on the future diffusion of opera images is analyzed. A parametric test was conducted on the predicted and actual values of the improved model to analyze whether there was a significant difference between the predicted and actual values and then to evaluate the prediction effect.

This model is considered scientifically sound when the evaluation results of both the improved model's fitting effect and prediction effect are good.

3.4 Diffusion improvement model construction

Assuming that the total number of members in the social system is a constant, all members in the social system during the proliferation of the opera image are divided into potential users and other users according to the nature of the users, and potential users are divided into adopted users and non-adopted users according to whether the users adopt the opera image or not. Taking the opera image with two iterations as an example, the evolution of the members in the social system is drawn, as shown in Figure 2.

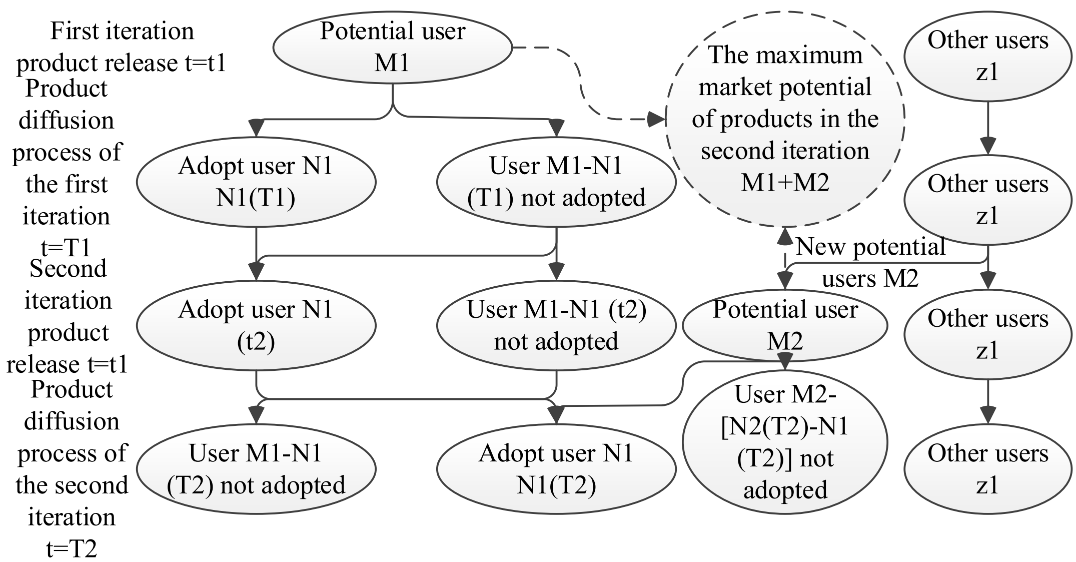


Figure 2. User evolution diagram during iterative diffusion

After the initial release of the opera stage makeup look, members within the social system are divided into other users and potential users, and only some of the members within the social system become potential users of the opera image. After the continuous proliferation of the opera image, the potential users gradually become adopted users, and the maximum market potential of the opera image is the sum of adopted and unadopted users. After that, to further expand the market, APP opera image publishers iterate and innovate the opera image, iterating new functions and forming new opera images based on the original opera image to cover the original opera image. The new opera image after the iteration opens up new market space among other users and gains new potential users, and the potential users of the 1st iteration opera image continue to spread and evolve. The maximum market potential of the opera image after the 2nd iteration is composed of the new potential users M2 of the opera image brought by the iteration and the existing potential users M1 of the opera image before the iteration.

According to the above analysis of the diffusion characteristics of the opera stage makeup model and the key influencing factors of the diffusion process, combined with the construction principle of the opera image diffusion improvement model, it is assumed that the iterative diffusion model of the opera stage makeup model is shown in Figure 3. The iterated opera image contains both the pre-iteration opera image function (a function I) and the post-iteration opera image function (function II), directly overwriting the version of the opera image that contains only function I before the iteration. According to the evolution diagram of iterative opera image users in Figure 2, it can be seen that the iterative opera image will attract some other users in the social system to become potential users of the iterative opera image, and the potential users of the pre-iteration opera image version continue the previous evolution. The new potential users brought by the iteration of the opera image and the potential users before the iteration of the opera image constitute the maximum market potential of the opera image.

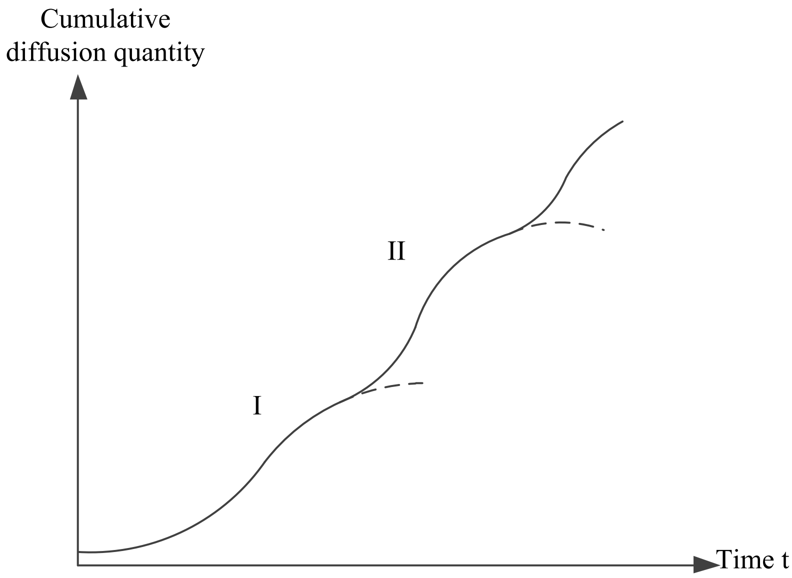


Figure 3. Iterative diffusion model of opera makeup creation

After a period of proliferation, the total potential market tends to be saturated, and the cumulative number of proliferation shows slow growth and is about to enter the dashed part of the curve, i.e., the stable stage of the life cycle. If the opera image is not iterated, the opera image diffusion curve will develop along the dashed part of curve I. When new features are added, and iterative innovations are made to the opera image according to users' needs or to explore users' potential needs, the iterated opera image will expand new markets and bring new potential users with the original market base, and the new iterated opera image will make a new round of diffusion among its potential users. The unadopted users among the potential users of the pre-iteration opera image also continue the previous diffusion. At this point, the process of opera image diffusion consists of two parts: one part is the new potential users expanded by the iterative innovation of the opera image, and the other part is the unadopted users among the potential users of the opera image before the iteration.

The iterative innovation of opera stage makeup modeling belongs to the overlay type. The opera image in stage I contains function I, and the image after carrying out iterative innovation has both functions I and function II in stage II. The diffusion curve II in Figure 3.2 is the diffusion curve of the iterative opera image after iteration, with functions I and II. The diffusion of the iterative opera image can be split into the diffusion of functions. Curve I am the diffusion curve of function I. The new function II is added to the iterative opera image after iteration, and a new diffusion is formed on the diffusion curve I of function I, which constitutes the diffusion curve II.

Considering the special nature of iterative innovation in opera stage makeup styling, the iterative diffusion model is shown below.

$$N_1(t)=F(t)M_1 \tag{11}$$

$$N_2(t)=F(t-\tau_2)M_2+F(t)M_1 \tag{12}$$

$$N_3(t)=F(t-\tau_3)M_3+F(t-\tau_2)M_2+F(t)M_1 \tag{13}$$

The above equation represents the diffusion model of the opera image with 3 iterations. Defining i as the number of iterations of the opera image, then $i=\{1,2,3,....\}$, the formula for the cumulative number of diffusion of the opera image that has undergone several iterations can be derived as:

$$N_i(t)=F(t-\tau_i)M_i+F(t-\tau_{i-1})M_{i-1}+F(t-\tau_2)M_2+F(t)M_1 \tag{14}$$

where $N_i(t)$ denotes the cumulative diffusion quantity of the opera image with i iterations t at the moment, M_i denotes the market potential of the opera image in the ith iteration, i.e., the number of potential users of the opera image in the ith iteration, and the maximum market potential of the opera image is $\sum_{n=1}^{i} M_i$. $F(t)$ is the cumulative diffusion rate of the Bass model, i.e., the ratio of the cumulative diffusion quantity to the maximum market potential at the t moment, and in the improved model denotes the ratio of the cumulative diffusion quantity of the opera image in the second iteration to its potential users at the moment, i.e., the ratio of $N_2(T_2)-N_1(T_2)$ to its potential users in Figure 2. The ratio of the cumulative diffusion of the image to its potential users, i.e., the ratio of $N_2(T_2)-N_1(T_2)$ to M_2 in Figure 2. τ_i denotes the time of the ith iteration of the opera image when $T \le \tau_i$ the $F(t-\tau_i)=0$.

The incremental potential users brought by the 2nd iteration of the opera image is M_2. $F(t)M_1$ represents the number of proliferation of the opera image before the iteration, i.e., the number of adopted users among the potential users of the opera image before the iteration, and this proliferation continues after the 2nd iteration of the opera image. The maximum market potential of the opera image after the 2nd iteration is composed of the new potential users M_2 of the opera image brought by the iteration and the existing potential users M_1 of the opera image before the iteration.

The analytical equation of $F(t)$ can be found from the Bass model equation:

$$F(t)=\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{15}$$

From equations (13) and (14), it can be seen that there is no substitution relationship between iterated products. There is also an implicit assumption that the innovation coefficient p and imitation coefficient q are the same for different iterative versions of the product, i.e., the product diffusion process is homogeneous for different iterative versions. According to the above analysis, it is clear that the actual product iteration diffusion process is heterogeneous because of the differences between different product iterations in terms of functionality and operation, i.e., the innovation coefficient p and the imitation coefficient q are different for different iterations of the product. Therefore, define p_i as the innovation coefficient of the ith iteration of the product q_i as the imitation coefficient of the ith iteration of the product, and the cumulative diffusion rate of the ith iteration of the product from Equation (15) is given by the following formula:

From equations (14) and (15), the iterative product diffusion model that takes into account the innovation coefficient and imitation coefficient of differentiated products, i.e., the iterative diffusion model applicable to APP products, can be obtained as follows:

$$N_1(t)=F_1(t)M_1 \tag{16}$$

$$N_2(t)=F_2(t-\tau_2)M_2+F_1(t)M_1 \tag{17}$$

$$N_3(t)=F_3(t-\tau_3)M_3+F_2(t-\tau_2)M_2+F_1(t)M_1 \tag{18}$$

Then the product diffusion model with i iteration is given by:

$$N_i(t)=F_i(t-\tau_i)M_i+F_{i-1}(t-\tau_{i-1})M_{i-1}+...+F_2(t-\tau_2)M_2+F_1(t)M_1 \tag{19}$$

In equations (18) and (19), time is the independent variable, the cumulative number of product diffusion is the dependent variable, and the parameters contain the potential users of the product in the ist iteration M_i, the innovation coefficient p_i, and the imitation coefficient q_i.

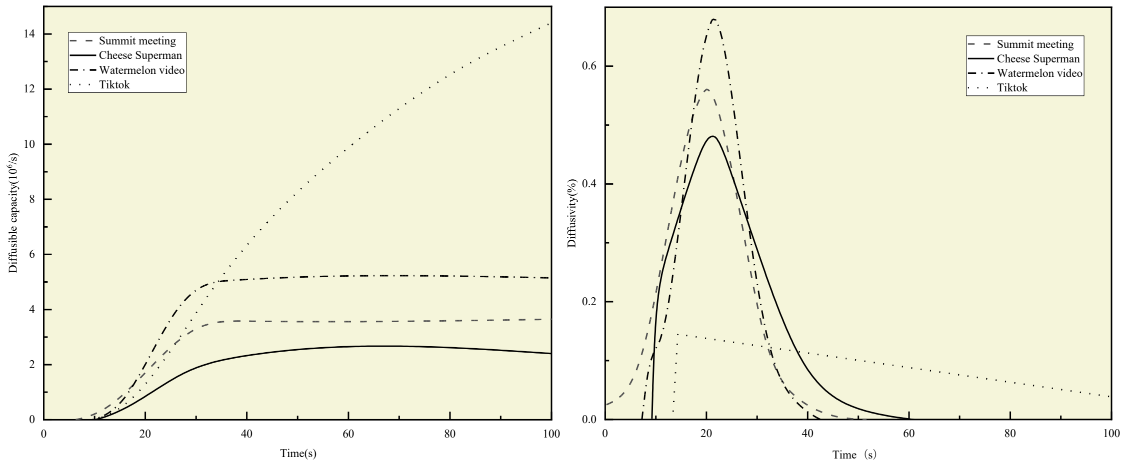
4 Case study of opera stage makeup modeling

Firstly, the data were processed, the new diffusion data were converted into cumulative diffusion data, and the model fitting and parameter estimation were performed by combining the above equations. The results of model fitting and parameter estimation for different time series data of products using 1stOpt software are shown in Table 2. The goodness of fit for all four products is greater than 0.9, which shows that the model fits well.

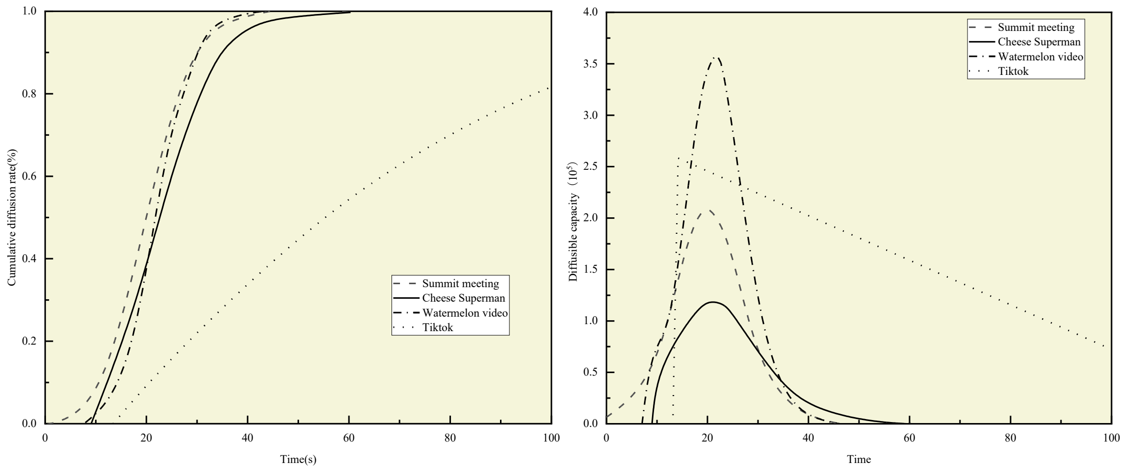
Table 2. Parameter estimation results of the four product diffusion models

Parameter items	Charge Conference	Cheese superman	Watermelon video	Jitterbug
Innovation coefficient p	0.0026	0.0193	0.0058	0.0146
Imitation coefficient q	0.2196	0.1542	0.2606	0.0103
Potential users M	3728827	2482375	5248458	17673976
Goodness-of-fit R^2	0.9964	0.9978	0.9998	0.9998

Based on the parameter estimation results in the above table, the fitted equation curves of cumulative diffusion, diffusion rate, cumulative diffusion rate, and diffusion for the four product diffusion models were drawn using Matlab software, as shown in Figure 4.



(a) Cumulative diffusion **(b)** Diffusivity



(c) Cumulative diffusion rate **(d)** Diffusion volume

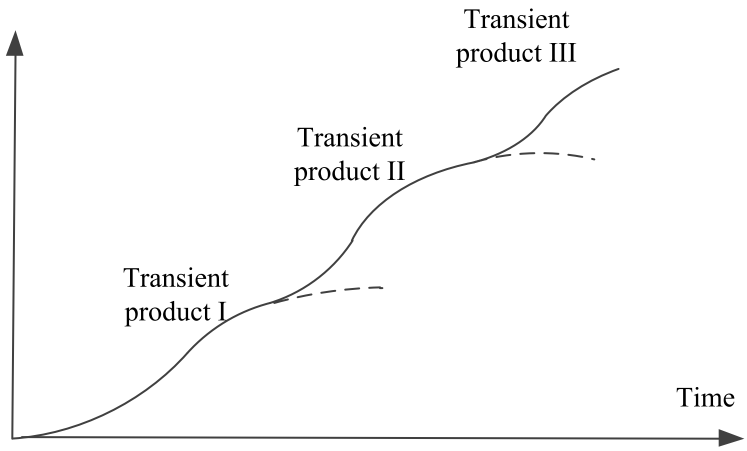
Figure 4. Fitting curve

The key factors affecting product diffusion are maximum market potential, external influences (innovation coefficient), and internal influences (imitation coefficient). The innovation and imitation coefficients determine the speed of product diffusion, and the maximum market potential determines the market competition of the product. The above four products, in order of the time to iterate the question-answering function, are Punching Contest, Watermelon Video, Cheese Superman, and TikTok.

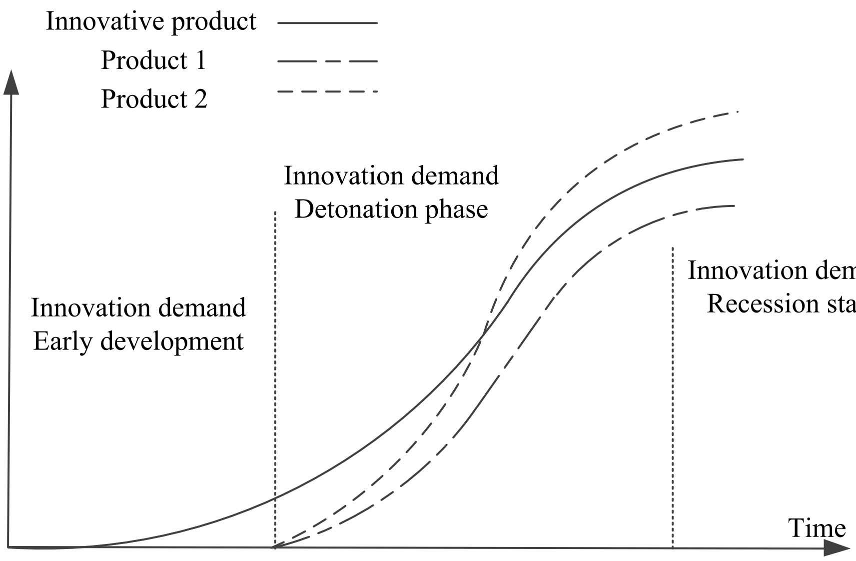
Figure 4(a) shows the curve of the cumulative diffusion volume fitting formula, in which Jitterbug's highest cumulative diffusion volume is 14. Figure 4(b) shows the curve of the product diffusion rate fitting formula, the initial diffusion rate of products are: Cheeseman, Jitterbug, Watermelon video, and Punchbowl in order from largest to smallest. Figure 4(c) shows the curve of the cumulative diffusion rate fitting formula, among which the diffusion rate of Jitterbug is 0.82, the lowest diffusion rate. Figure 4(d) shows the fitted formula curve of diffusion volume, among which the diffusion volume of the watermelon video is 3.6, with the highest diffusion volume. When innovative technology enters the market for the first time, consumers hold a wait-and-see attitude toward the innovative technology leading to slow diffusion of the initial innovation and gradually overcoming the initial diffusion inertia with the increase of market recognition and the increase of the number of users.

According to the parameter estimation results of the four products above, the maximum market potential after iterating the question-answering function is, in descending order, Jitterbug, Watermelon Video, Topping Contest, and Cheeseman. As the first product to innovate the question-answer model, Punching Top has the first-mover advantage in terms of product and function, while Cheeseman, released after Punching Top with the same function, has the follower advantage. Based on the parameter estimation results, we can see that the maximum market potential of the Punching Contest is larger than Cheeseman, and we believe that the competitive advantage between Punching Contest and Cheeseman is the first mover advantage. Watermelon Video and Jitterbug both iterated the question-answering function after Punchbowl, and both products iterated the new product version with a question-answering function based on the original product function, so they have the product-level first-mover advantage, while Punchbowl has a the function-level first-mover advantage.

The theatrical image publisher constantly innovates products in response to changing user needs and rapidly iterates on products and processes to improve product attractiveness, attract more users, and expand new market space. Product iteration brings incremental market potential, increases the product's maximum market potential, and extends the product life cycle. The life cycle curve of the opera image is not a smooth development, and the product constantly iterates and innovates to form a transient product, driving the fluctuating evolution of the life cycle curve. As shown in Figure 5.



(a) Diagram I



(b) Diagram II

Figure 5. On the cycle of improvement and innovation of stage makeup styling in opera

It can be seen from Figure 5 that Product 1 and Product 2 imitate the function after the innovative product, assuming that Product 1 is newly released and does not have the product-level first-mover advantage, while Product 2 iterates based on the original product and has the product-level first-mover advantage. The innovative product and product one are both newly released, and the innovative product is the first mover in the market. The product's adaptability effect can lead to incremental user benefits. Hence, the competitive advantage between the innovative product and product one is the innovative product's first-mover advantage, and the innovative product and the proliferation of the innovative product is greater. Product II carries out product iterations with a user base, and the larger the user base and the greater the product network effect, the greater its competitive advantage. Therefore, the competitive advantage between the innovative product and product two is expressed as product two's product-level predominance and product two's proliferation is greater.

At the early stage of innovation demand development, users hold a wait-and-see attitude towards innovative features, resulting in a slow proliferation of innovative products at this stage. With the increase in market recognition and the number of users, the initial proliferation inertia is gradually overcome, and the product proliferation speed increases as other products in the market imitate and issue new products with the same functions or iterate the same functions based on the original products; in the declining stage of innovation demand, the market tends to be saturated, and the product proliferation speed slows down, so the product publishers can iterate the products The product publisher can iterate the product, innovate, explore or create new user needs, and promote a new round of product proliferation.

5 Conclusion

Web servers store huge amounts of data, and after being organized and analyzed by big data, they are used to solve various complex problems, and theater communication is among them. Therefore, this paper uses big data to analyze and study the current theater communication or to provide new ideas and open up new paths for the future development of theater. By setting five audience feedback indicators to analyze the influencing factors of drama communication, we can get which indicator has a greater impact on drama communication and which medium is more suitable for the dissemination and development of drama. The product diffusion data empirically analyzes the product iterative diffusion model. The results show that the product iterative diffusion model has a better fitting and prediction effect.

Furthermore, compared with the fitting effect and prediction effect of the Bass model, the results prove that the improved model has a better fitting effect and prediction effect on product diffusion. The highest cumulative diffusion of TikTok is 14, and the diffusion rate of the Watermelon video is 0.68. According to the parameter estimation results of the diffusion model, product iteration innovation can attract new users, create new markets and increase the maximum market potential of products.

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