ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

# Research on Demand Diffusion of Airline Tickets based on Social Media

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## Abstract

**Leveraging the strong social attributes of social media platforms, airline ticket products can be rapidly disseminated through user interactions, significantly enhancing the efficiency of information delivery in online social networks. This study focuses on the demand diffusion process of airline tickets, taking Shenzhen Airlines' live-streaming rooms as the research subject. By collecting bullet comments and user behavior data, we classify users into four states: Potential Spreader (P), Observer (O), Potential Buyer (B), and Discarder (D). An improved SEIR epidemic model is constructed to simulate the diffusion of product information. Model parameters are estimated using the least squares method based on real data. The influence of key factors such as information propagation rate and product attractiveness on demand diffusion is analyzed through numerical simulations. The results provide theoretical guidance for airlines to optimize their social media marketing strategies.**

## Keywords

**Airline Ticket; Demand Diffusion; Social Media; SEIR Model; Parameter Estimation.**

## 1. Introduction

Relying on the powerful social attributes of social media platforms, travelers can complete the entire process of obtaining, understanding, and purchasing airline ticket products through online social platforms, significantly improving the efficiency of information delivery in online social networks. [1] This communication advantage helps expand the airline ticket market. Through social platforms, potential travelers can obtain flight information, query and learn about ticket products, or make purchases, which stimulates their continuous attention to product information and thus promotes effective demand conversion. [2,3]While browsing platforms with both social and shopping attributes such as Douyin and Taobao, users can choose whether to enter a live-streaming room to learn about airline ticket products, further making purchase decisions or discarding information and exiting the live room. During this process, travelers have the opportunity to obtain, understand, and even disseminate airline ticket information in their spare time. Airlines rely on online platforms to achieve the diffusion of product information among groups. According to the grounded theory research conclusions in this paper, the main factors stimulating user demand and information diffusion include product attractiveness and social communication context. However, the specific quantitative impact mechanisms of these factors on the demand diffusion process remain unclear, so it is necessary to systematically sort out their effects.[4,5]

This paper focuses on the modeling of the demand diffusion process for airline ticket products, incorporating the product attractiveness extracted from grounded theory analysis into the subsequent quantitative analysis framework. [7]Product information can be regarded as content transmitted and acquired by users in social interactions, while ticket purchase behavior

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

corresponds to the adoption and conversion of information. In the field of information dissemination research, the classic SEIR epidemic model is often used to characterize the law of information diffusion in networks. This paper adopts this modeling approach to construct a demand diffusion model suitable for airline ticket products, simulating the dissemination dynamics of product information. Through parameter sensitivity analysis, the degree of influence of various factors on demand diffusion is evaluated. In the information dissemination process, the attractiveness of the information itself to recipients significantly affects the breadth and depth of dissemination. Similarly, airline ticket products differ in price, route, service, etc., resulting in different attractiveness to users. These attractiveness differences will affect users' choices after being exposed to product information-whether to continue paying attention, purchase, or give up-thereby directly affecting the overall diffusion trend of product demand. This chapter focuses on constructing a basic demand diffusion model and analyzing the demand diffusion process of airline ticket products in a single-community social network.

## 2. Model Construction

### 2.1. Demand Diffusion Process of Airline Ticket Products in a Single-community Structure

Consumer cognition of purchased products includes two aspects: first, when consumers have not experienced the product and do not understand the product, they obtain product cognition through external information and make decisions to further understand the product; second, cognition generated during the process of understanding the product, which affects consumers' intention to use. The process is shown in Fig. 1. In the era of highly developed social media, enterprises often maximize the spread of the first layer of cognition through promotions in social media, and then enhance users' purchase intention and user stickiness by improving their perception of products and services. In the context of airline ticket products, this is specifically reflected in airlines disseminating ticket product information through social media and online sales platforms, and travelers learning about airline ticket products through anchor explanations and bullet comments from other users, thereby driving travel demand.

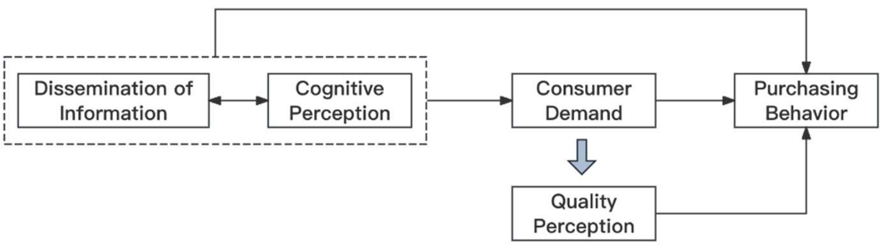


**Fig. 1** influence path from information recognition to consumer demand

Airline ticket product information spreads in social networks. Users in the network choose whether to accept the product information, decide whether they are willing to learn about the product, and decide whether they are willing to purchase the product. [8][10]Hereinafter, "product" refers to airline ticket products. Based on the user cognition process, the process of airline ticket demand driven by information dissemination is shown in Fig. 2. Information dissemination leads users to form cognition of the product, triggers willingness to further understand the product, and then, through factors such as product service performance, forms a good user experience leading to purchase behavior. This study divides the above process into two stages: information dissemination and purchase decision, and constructs a propagation model to explore the time evolution of the number of each type of individual in this process. In

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the figure, P, O, and B represent node states, and their specific meanings will be explained in detail in the propagation model.

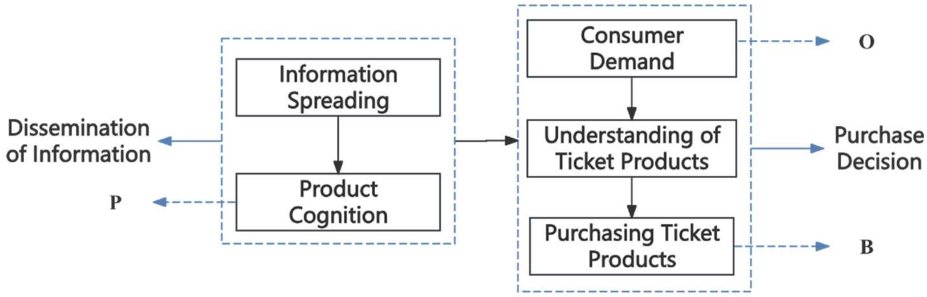


**Fig. 2** air ticket product demand motivated by information diffusion

Since the airline ticket product market with interactive behavior is similar to the infectious disease system with a large number of interacting individuals, and as mentioned earlier, the epidemic model can effectively simulate information dissemination, user cognition, and purchase decision propagation, this study proposes a continuous-time Markov process based on the propagation mechanism of the epidemic model to study the impact of information dissemination on the demand diffusion of airline ticket products. [9][12]The demand diffusion process is shown in the following figure.

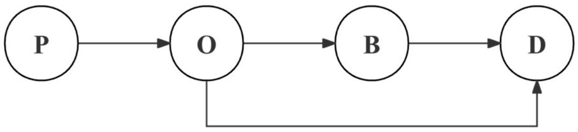


**Fig. 3** demand diffusion process of air ticket product

The research object of this model is airline ticket products. At the level of information acquisition channels, online sales platforms, social media, online forums, etc., have become the main sources of product information.[10][11] As a demand diffusion model for airline ticket products, this model has both connections and differences with general product demand diffusion models. The connection is that both airline ticket products and traditional products can have observation and purchase behaviors. The difference is that due to the lack of basic cognition of airline ticket products, users need further understanding before they generate purchase behavior for airline ticket products. In summary, this model is suitable for studying the cognition and purchase of airline ticket products in the context of social networks.

The model simulates the process of users interacting through online social media and disseminating product information to each other with a certain probability. It mainly considers the spread of a single information source among multiple users, and the transmission mode between users is one-to-one. The model considers the information dissemination and discarding processes of potential recipients. It assumes that the connection probabilities between nodes in the network are equal, and each node has the same credibility and influence. At the same time, product information is exogenous to the social network, and information acquisition costs are not considered.[13]As shown in Fig. 3, each node in the figure represents a state type, and each node can only be in one state at a time.

The consumers of airline ticket products on social media platforms are divided into four states. Potential Spreader (P): Users who have not yet received airline ticket product information.

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

Nodes in this state do not have the ability to spread information. Abbreviated as P users. Observer (O): Users who have received airline ticket product information and entered an observation state. Nodes in this state carry information and have the ability to spread it. Abbreviated as O users. Potential Buyer (B): Users who have developed purchase intention after continuous observation. Nodes in this state carry information and have the ability to spread it. Abbreviated as B users. Discarder (D): Users who discard information and exit the purchase and information dissemination process. Nodes in this state do not have the ability to spread information.

State transitions: (1) P → O: After receiving product information, nodes become interested in the information and continue to understand the product. (2) O → B: Due to further understanding of the product, O nodes choose to purchase the product with a certain probability. (3) O → D: Due to perceived product risk or other reasons, they refuse to purchase the product and no longer spread information. (4) B → D: After purchasing the ticket product and having no short-term need for repeat purchase, they discard the information and exit the dissemination process.

## 2.2. Construction of the Demand Diffusion Model for Airline Ticket Products in a Single-community Structure

Let the numbers of Potential Spreaders, Observers, Potential Buyers, and Discarders at time t be denoted as $P(t)$, $O(t)$, $B(t)$ and $D(t)$, respectively. To investigate the state transition process of nodes, define a series of indicator functions to represent the state transition events of nodes within the time interval $(t, t + \Delta t)$. When the indicator function takes the value 1, it indicates that the node state transition occurs; when it takes 0, it indicates no transition. [6]The specific functions and the events they indicate are shown in Table 1.

**Table 1.** interpretation of indication functions

| Indication Functions | Event |
|---|---|
| $\varphi_j(t, t + \Delta t)$ | Whether node changes from state P to state O |
| $\omega_j(t, t + \Delta t)$ | Whether node changes from state O to state D |
| $\theta_j(t, t + \Delta t)$ | Whether node changes from state O to state B |
| $\psi_j(t, t + \Delta t)$ | Whether node changes from state B to state D |

Let $\{P(t)\}$ be the set of all nodes in state P at time t, and $\{O(t)\}$ be the set of all nodes in state O at time t. The change in the number of O nodes can be expressed as follows:

$$O(t + \Delta t) = O(t) + \sum_{j\in\{P(t)\}} \varphi_j(t, t + \Delta t) - \sum_{j\in\{O(t)\}} \omega_j(t, t + \Delta t) - \sum_{j\in\{O(t)\}} \theta_j(t, t + \Delta t) \quad (1)$$

Consumers obtain information through online live rooms, social platforms, etc. During this process, consumers have a certain probability of spreading airline ticket product information to each other. [13]Since whether information transmission occurs between consumers in mutually exclusive time intervals is an independent event, the occurrence of information transmission events can be regarded as a Poisson process, and its waiting time follows an exponential distribution.[14][15] Define $\beta$ as the parameter measuring the probability of information transmission. Assume that within the $\Delta t$ period, the node contact probability follows an exponential distribution with parameter $\beta$. Then, the probability of an information spreader transmitting information per unit time is $\beta$. The nodes with transmissible include O and B, with corresponding numbers $O(t)$ and $B(t)$. Therefore, the transmission probability per

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unit time is the product of $\beta$ and the number of spreaders, and the time required for node conversion follows an exponential distribution with parameter $\beta[O(t)+B(t)]$.The probability of a node transitioning from P to O is:

$$P(\varphi_j(t,t+\Delta t)=1)=1-e^{-\beta(O(t)+B(t))\Delta t} \tag{2}$$

$\mu$ is assumed as the initial information discard rate, measuring the probability of O nodes discarding information. Similarly, assume that the probability of O nodes discarding information and becoming D nodes follows an exponential distribution with parameter $\mu$. $\sigma$ is the product attractiveness, characterizing the probability of O nodes further understanding the airline ticket product and purchasing it. Assume that the probability of O nodes transitioning to B nodes follows an exponential distribution with parameter $\sigma$. Similarly, $\gamma$ is assumed as the final information discard rate, characterizing the probability of B nodes discarding information. Assume that the probability of B nodes transitioning to D nodes follows an exponential distribution with parameter $\gamma$. Then the node transition probabilities are:

$$P(\omega_j(t,t+\Delta t)=1)=1-e^{-\mu\Delta} \tag{3}$$

$$P(\theta_j(t,t+\Delta t)=1)=1-e^{-\sigma\Delta} \tag{4}$$

$$P(\psi_j(t,t+\Delta t)=1)=1-e^{-\gamma\Delta t} \tag{5}$$

Combining with equation (1), change in the number of O nodes can be obtained as:

$$O(t+\Delta t)=O(t)+P(\varphi_j(t,t+\Delta t)=1)\cdot P(t)-P(\omega_j(t,t+\Delta t)=1)\cdot O(t) \\ -P(\theta_j(t,t+\Delta t)=1)\cdot O(t) \tag{6}$$

Substituting equations (2)-(4) into (6), the rate of change of the number of observers who have been exposed to ticket product information per unit time is:

$$\lim_{\Delta t\to 0}\frac{O(t+\Delta t)-O(t)}{\Delta t} \tag{7}$$
$$=\lim_{\Delta t\to 0}\frac{1}{\Delta t}\left[\left(1-e^{-\beta(O(t)+B(t))\Delta t}\right)\cdot P(t)-\left(1-e^{-\mu\Delta t}\right)\cdot O(t)-\left(1-e^{-\sigma\Delta t}\right)\cdot O(t)\right]$$

$$\frac{dO(t)}{dt}=\beta[O(t)+B(t)]\cdot P(t)-\mu\cdot O(t)-\sigma\cdot O(t) \tag{8}$$

Information dissemination turns potential spreaders into observers, and some P nodes become O nodes. The change in P nodes is:

$$P(t+\Delta t)=P(t)-\sum_{j\in\{P(t)\}}\varphi_j(t,t+\Delta t) \tag{9}$$

Combining with equation (9), the change in the number of P nodes can be expressed as:

$$P(t+\Delta t)=P(t)-P(\varphi_j(t,t+\Delta t)=1)\cdot P(t) \tag{10}$$

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Substituting equation (2) into (10), the rate of change of the number of spreaders who have not been exposed to ticket product information per unit time is:

$$\lim_{\Delta t\to 0}\frac{P(t+\Delta t)-P(t)}{\Delta t}=\lim_{\Delta t\to 0}\frac{-1}{\Delta t}\left[\left(1-e^{-\beta(O(t)+B(t))\Delta t}\right)\cdot P(t)\right] \tag{11}$$

$$\frac{dP(t)}{dt}=-\beta[O(t)+B(t)]\cdot P(t) \tag{12}$$

Continuous information dissemination leads observers O to purchase ticket products and become B nodes or discard product information and become D nodes. Some potential buyers B discard information and become D nodes after receiving the information. The changes in the numbers of B and D nodes are:

$$B(t+\Delta t)=B(t)-\sum_{j\in\{B(t)\}}\psi_j(t,t+\Delta t)+\sum_{j\in\{O(t)\}}\theta_j(t,t+\Delta t) \tag{13}$$

$$D(t+\Delta t)=D(t)+\sum_{j\in\{O(t)\}}\omega_j(t,t+\Delta t)+\sum_{j\in\{B(t)\}}\psi_j(t,t+\Delta t) \tag{14}$$

$$B(t+\Delta t)=B(t)-P(\psi_j(t,t+\Delta t)=1)\cdot B(t)+P(\theta_j(t,t+\Delta t)=1)\cdot O(t) \tag{15}$$

$$D(t+\Delta t)=D(t)+P(\omega_j(t,t+\Delta t)=1)\cdot O(t)+P(\psi_j(t,t+\Delta t)=1)\cdot B(t) \tag{16}$$

Substituting equations (4) and (5) into (15), the rate of change of the number of potential buyers per unit time is:

$$\lim_{\Delta t\to 0}\frac{B(t+\Delta t)-B(t)}{\Delta t}=\lim_{\Delta t\to 0}\frac{1}{\Delta t}[(1-e^{-\sigma\Delta t})\cdot O(t)-(1-e^{-\gamma\Delta t})\cdot B(t)] \tag{17}$$

$$\frac{dB(t)}{dt}=\sigma\cdot O(t)-\gamma\cdot B(t) \tag{18}$$

Substituting equations (3) and (5) into (16), the rate of change of the number of discarders per unit time is:

$$\lim_{\Delta t\to 0}\frac{D(t+\Delta t)-D(t)}{\Delta t}=\lim_{\Delta t\to 0}\frac{1}{\Delta t}[(1-e^{-\mu\Delta t})\cdot O(t)+(1-e^{-\gamma\Delta t})\cdot B(t)] \tag{19}$$

$$\frac{dD(t)}{dt}=\mu\cdot O(t)+\gamma\cdot B(t) \tag{20}$$

Through the rates of change of P, O, B, D nodes, i.e., equations (8), (12), (18), and (20), the dynamic equations are constructed to characterize the demand diffusion process of airline ticket products within the community. The demand diffusion model is as follows:

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$$\begin{cases} \frac{dP(t)}{dt} = -\beta[O(t)+B(t)]\cdot P(t) \\ \frac{dO(t)}{dt} = \beta[O(t)+B(t)]\cdot P(t) - \mu\cdot O(t) - \sigma\cdot O(t) \\ \frac{dB(t)}{dt} = \sigma\cdot O(t) - \gamma\cdot B(t) \\ \frac{dD(t)}{dt} = \mu\cdot O(t) + \gamma\cdot B(t) \end{cases} \quad (21)$$

# 3. Demand Diffusion Effects and Influencing Factor Analysis for Single-Community Airline Tickets

## 3.1. Network Data Collection and Processing

This study uses Python to collect bullet comments and product information from live-streaming rooms. Shenzhen Airlines was selected as the information dissemination subject because of its high live-streaming frequency, long explanation time, high popularity ranking, wide route coverage, and public user information. To avoid bias caused by viewers who are either too knowledgeable or completely ignorant of aviation products, the study excludes ancillary service products such as lounge vouchers, in-flight Wi-Fi vouchers, and pet-in-cabin service vouchers, which are unrelated to travel. To eliminate bias due to airline attributes and ticket price differences, a full-service airline with relatively stable ticket prices was chosen. User information in Shenzhen Airlines' live rooms is public, facilitating viewer information collection. User IDs were anonymized, and no sensitive personal information was stored. Bullet comments were crawled every 10 minutes to monitor viewer numbers, online counts, ticket product sales, and product information discussions.

To eliminate the influence of seasonal and holiday factors, this study collected information from 33 live sessions of Shenzhen Airlines from June 20, 2025, to March 17, 2026, including online viewer numbers, product sales, and bullet comments related to ticket product inquiries. To ensure effective information reach and sustained influence on live room viewers, 11 live sessions that simultaneously met three conditions-duration of 5 hours or more, more than 10,000 viewers, and ranking in the top 10 of the group buying list-were selected as research objects. The crawled texts were stored in CSV format for subsequent data processing and statistics.

**Table 2.** the content of indicated bullet comments

| Session | Time | User | Bullet Content |
|---|---|---|---|
| 20250626 | t=7 | Xiaosheng | Is there Haikou to Shenzhen? |
| | | Yuanli MM | Shenzhen to Nantong, Nantong to Shenzhen |
| | | Xiao Xiao | What is the validity period? |
| | t=37 | Erhai | For the international round-trip pass, do I need to buy two? |
| | | alphonso | Does the voucher I just bought need to be used after three days? |
| | | Miwang | I bought it, but when I clicked in, it showed fully redeemed |
| | t=97 | zx | Just redeem it on the official website three days in advance, right? |
| | | Paradox | Can the 499 voucher be used to buy for others? |
| | | Tianri | Will the flights be replenished after redemption? |

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The bullet comment data contained various English characters, internet symbols, and texts that were too short or contained no information; these were removed through data cleaning. After cleaning, a total of 350,683 bullet comments relevant to this study were obtained. The 11 live sessions on different dates were unified on a time scale, retaining 5 hours of bullet comment information, and divided into 0 to 300 minutes. The discussion content of each live room at different time periods was obtained. Some bullet comment examples are shown in Table 2.

Since this study needed to obtain bullet comments from the same user at different time points, we inferred from the bullet content whether the user received ticket information, whether they were willing to further learn about airline ticket products, and whether they generated purchase intention. Based on the bullet content, users were classified into one of the four states: P, O, B, D. According to the time points when users were in different states, the number of nodes in each state at different time points was calculated. Based on these counts, the information propagation rate, product attractiveness rate, initial discard rate, and final discard rate were estimated.

## 3.2. Parameter Estimation

In existing propagation dynamics models, parameter values are often determined based on subjective judgment or past experience, failing to fully consider the actual context of information dissemination. To enable the model to effectively simulate the product demand diffusion process, this study uses the least squares method for parameter estimation based on real data.

Based on the bullet comment information, the number of nodes at each time point was counted. The number of viewers discussing ticket products within each time period was regarded as the number of observers ; the number of viewers discussing the conditions for using flight passes was regarded as the number of potential buyers ; the number of viewers who sent only one bullet comment and did not participate in subsequent discussions was regarded as the number of discarders. Assuming that the number of viewers entering and exiting the live room per unit time is equal, the average online viewers was taken as the total number of people in the live room, and the number of potential spreaders  was further calculated.

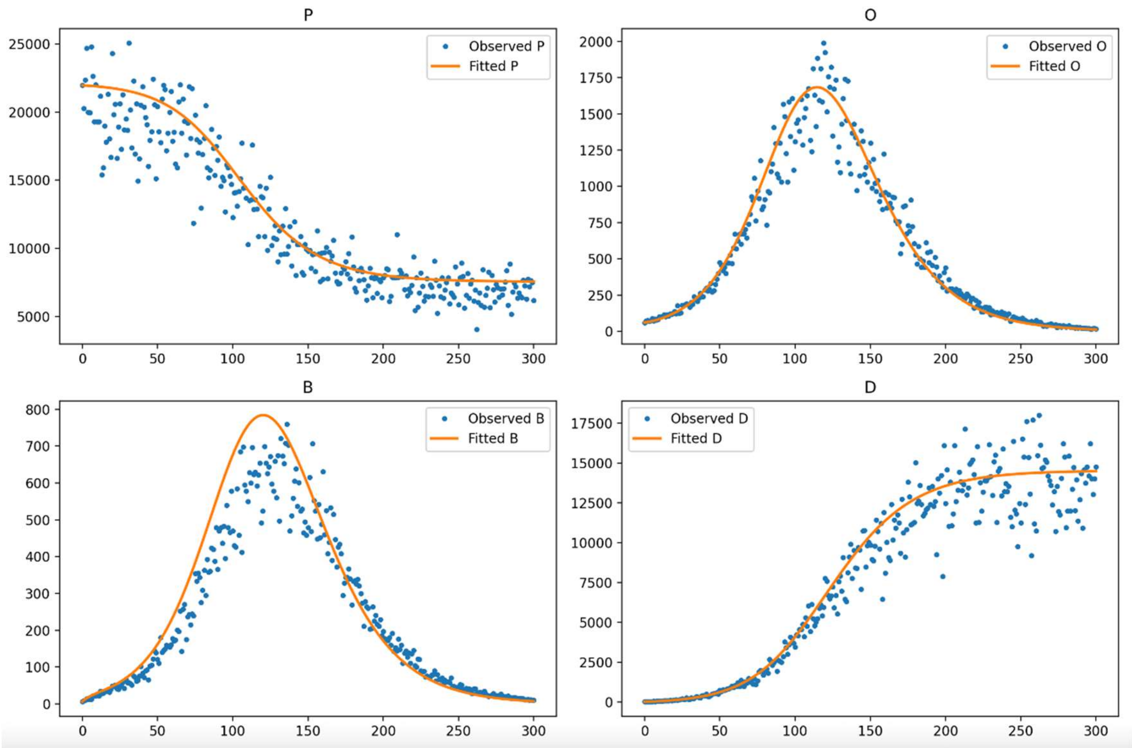


**Fig. 4** comparison between theoretical and simulation results

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

The demand diffusion model contains a parameter vector to be estimated. Given the initial state vector , the differential equations are solved numerically using an ODE solver to obtain the model predictions at each time point . The sum of squared residuals between the model predictions and the observed data, , is minimized as the fitting criterion. When the residual sum of squares converges to a minimum, the corresponding is the optimal parameter estimate.[6]

The above process was implemented in Python. The odeint function was used to obtain the prediction curves, and least_squares was used to adjust the parameters to minimize the residual sum of squares. The parameter estimates and goodness-of-fit were calculated. The curve fitting results are shown in Fig. 4.

The parameter estimation results are shown in Table 3.

**Table 3**. parameter estimation result

| Parameter | Range | Estimated Value |
|---|---|---|
| $\beta$ | (0,1) | 0.091047 |
| $\mu$ | (0,1) | 0.092293 |
| σ | (0,1) | 0.082298 |
| γ | (0,1) | 0.074696 |

## 3.3. Information Dissemination and Demand Diffusion Analysis

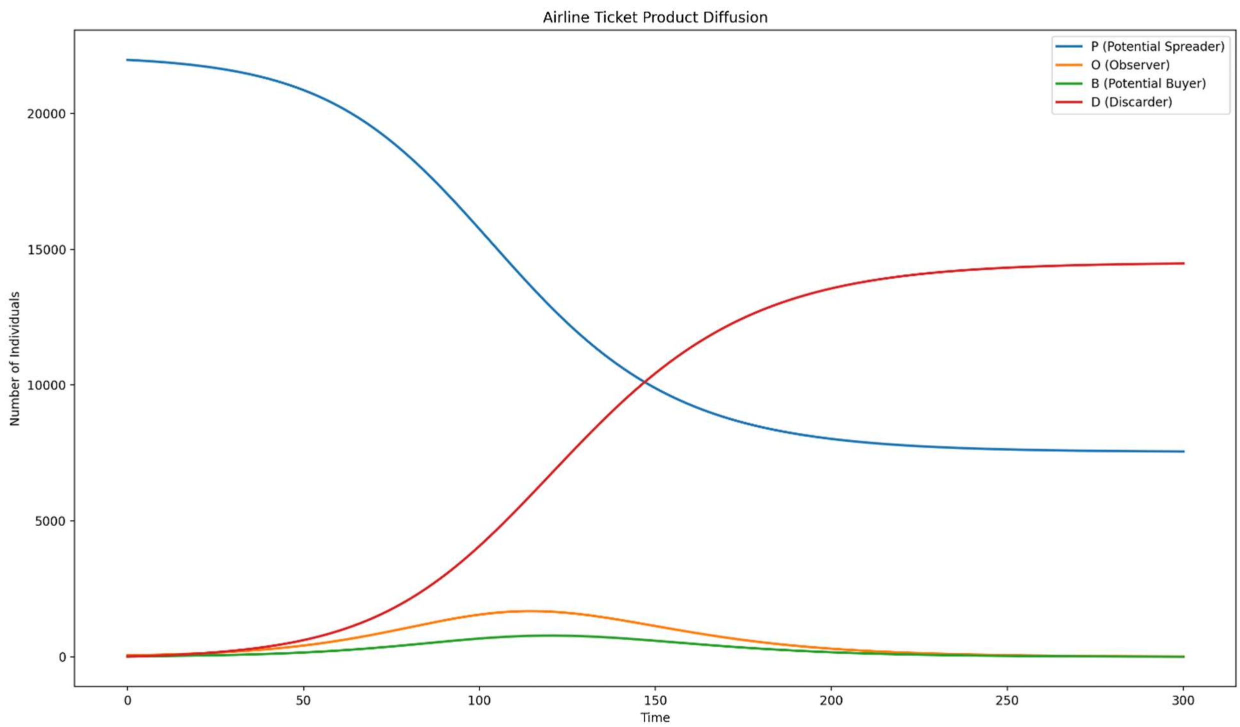


**Fig. 5** illustration of time evolution of number of nodes

According to the demand diffusion mechanism proposed in the previous section, simulation was carried out to show the dynamic evolution of the four user groups during the information dissemination process. [17] Figure 5 intuitively shows the changes in the numbers of the four types of users over time. The number of P nodes (potential spreaders) decreases rapidly in the initial stage. The numbers of O nodes (observers) and B nodes (potential buyers) slowly increase to a peak and then gradually decrease to zero. The number of D nodes (discarders)

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

increases sharply in the early stage, then stops growing and enters a stable period in the middle and late stages, showing an S-shaped growth curve. Under the above parameter settings, after the dissemination reaches a steady state, the proportion of B nodes in the system is 12.37%, as shown in Fig. 5.

## 3.4. Influence of Information Propagation Rate

The time evolution of the demand diffusion of ticket products under different parameter settings is studied below. The proportion of observer nodes at time t is used to evaluate the degree of information diffusion of ticket products, calculated as:

$$r(t) = \frac{B(t)}{N} \tag{22}$$

Exploring the influence of the information propagation rate on the proportion of potential buyers, $r(t)$ rises sharply to 0.22 in a very short time, indicating rapid information spread and quick influence on some viewers. As shown in Fig. 6, the curve exhibits typical characteristics of rapid start, slow growth, and eventual dynamic equilibrium, reflecting the process from outbreak to saturation of information dissemination.

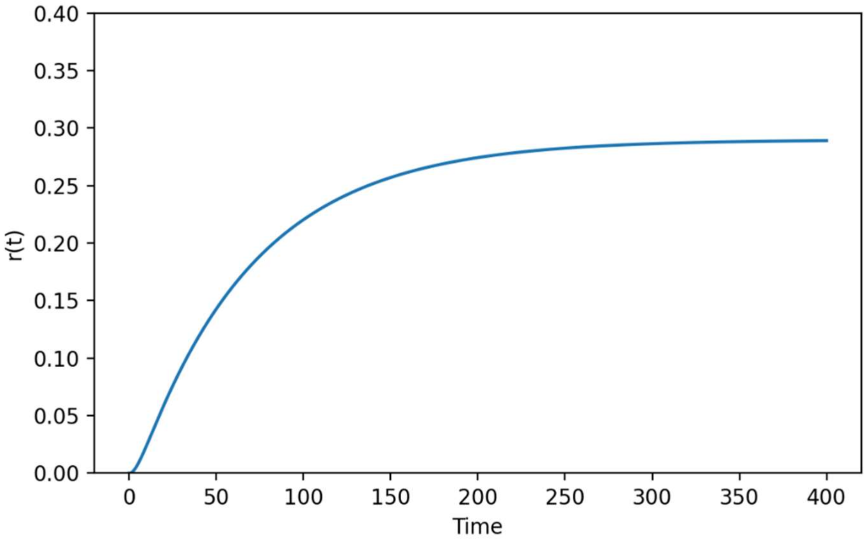


**Fig. 6** situation of demand diffusion

Fig. 7 shows the time evolution of $r(t)$ under different information propagation rates. The larger the $\beta$ value, the faster the curve rises and the higher the final stable value. All curves show S-shaped growth, accelerating in the early stage and gradually leveling off. With the increase of the information propagation rate, the outbreak time of diffusion is advanced, the node growth rate increases, but the final scale of $r(t)$ is not greatly affected. When the information propagation rate is small, increasing it can significantly expand the demand diffusion range; however, when it increases to a certain critical value, further increasing the parameter no longer increases the dissemination scale.

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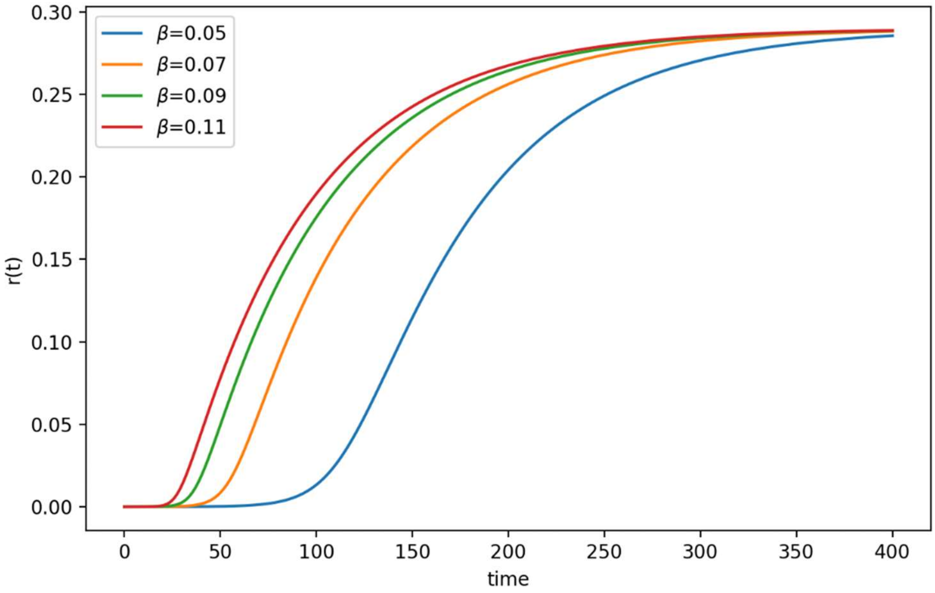


**Fig. 7** influence of information diffusion rate on r(t)

As shown in Fig. 8, when the information propagation rate is small, increasing it significantly expands the demand diffusion range; when it increases to a certain critical value, further increasing the parameter no longer increases the purchase demand scale. This critical value is related to the total dissemination time. The longer the total dissemination time, the smaller the critical value. Moreover, regardless of the value of the information propagation rate, extending the dissemination time can always significantly increase the proportion of repeat buyers.

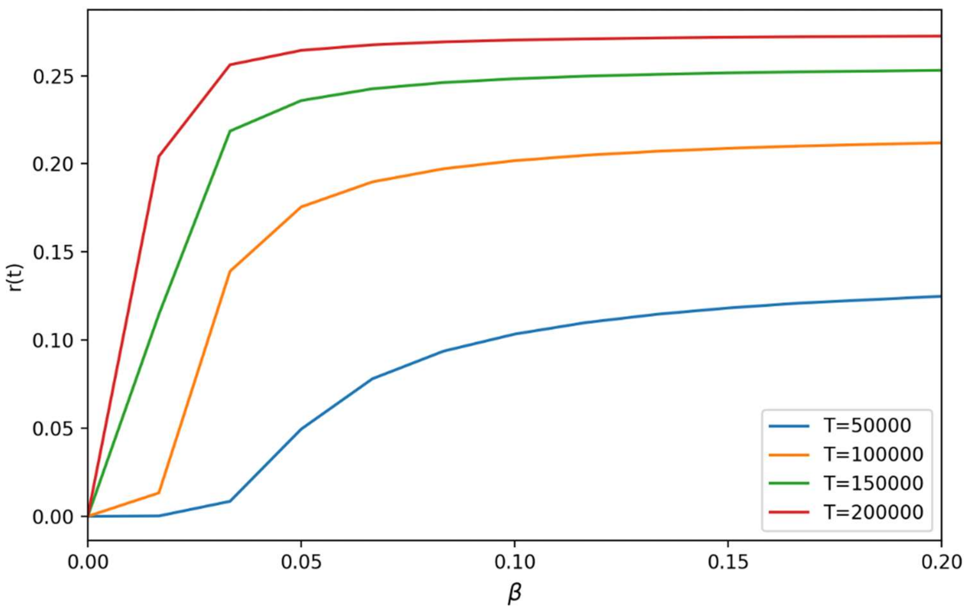


**Fig. 8** influence of information diffusion rate on r(t)

## 3.5. Influence of Product Attractiveness

When observers obtain product information, they can decide whether to continue learning about the product. The parameter is adjusted to explore the influence of product attractiveness. Fig. 9 shows the time evolution of the proportion of B nodes under different attractiveness

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

values. As continues to increase, the marginal promotion effect of increasing on dissemination diminishes.

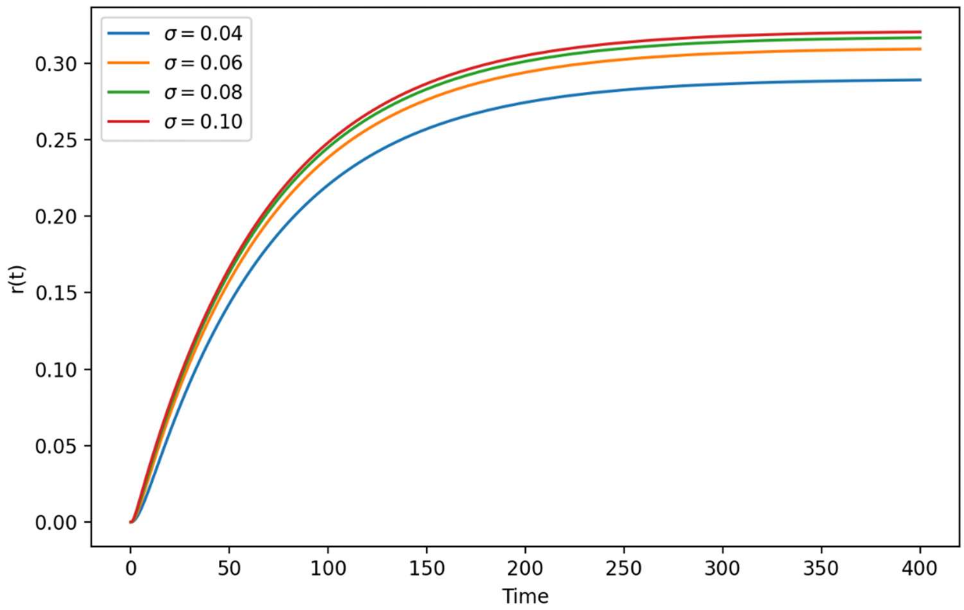


**Fig. 9** impact of attractive on demand diffusion

Fig. 10 shows the relationship between and attractiveness under different total durations. As increases, increases sharply in the initial stage. When the duration is short, extending the total dissemination time significantly increases. When considering promotion strategies targeting travelers, extending the promotion time within a certain range helps to increase the scale of demand diffusion.

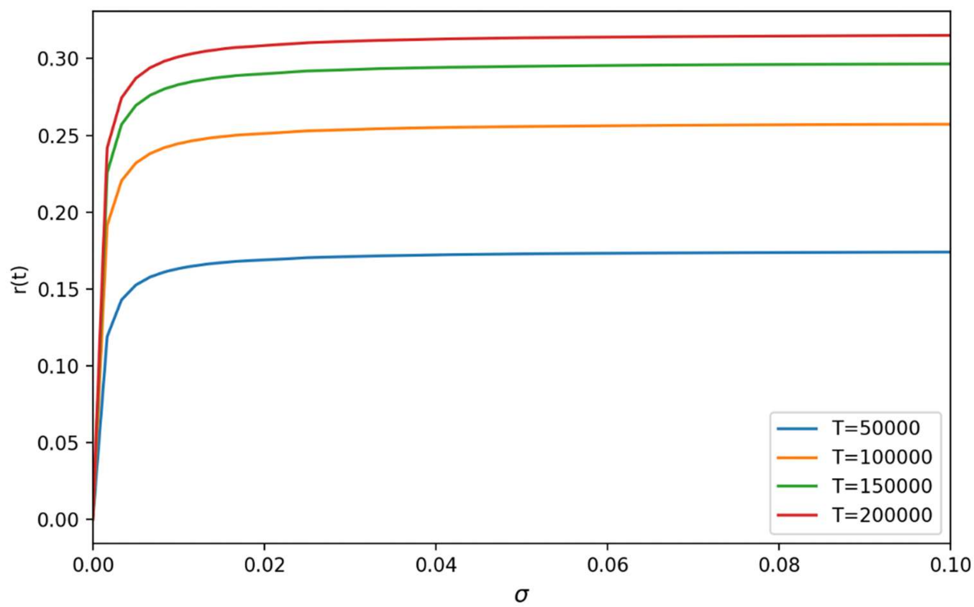


**Fig. 10** impact of attractive on demand diffusion

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

## 4. Discussion

This study constructed an improved SEIR-type model to simulate the demand diffusion process of airline ticket products on social media platforms. Using real bullet comment data from Shenzhen Airlines' live-streaming rooms, we classified users into four states and estimated model parameters via least squares. The main findings are as follows:

Information propagation rate: A higher accelerates the outbreak of diffusion and increases the growth rate of , but its impact on the final diffusion scale is limited. There exists a critical value beyond which further increase in does not significantly enhance demand diffusion. Moreover, extending the total dissemination time can always increase the final proportion of potential buyers.

Product attractiveness: Increasing promotes the conversion from observers to potential buyers, but the marginal effect diminishes as becomes larger. For short promotion periods, extending the time can significantly improve the effect of attractiveness.

User state evolution: The dynamics show that P nodes decline rapidly, O and B nodes rise to peaks and then decline, while D nodes increase in an S-shaped curve, consistent with typical information diffusion patterns.

Model validation: The fitted curves match the observed data well, with $R^2$ values indicating good model performance. The estimated parameters fall within reasonable ranges, confirming the validity of the model.

## 5. Conclusion

From the perspective of information dissemination driving consumer demand, a basic demand diffusion model for ticket products is constructed, taking into account information dissemination in social networks. Based on the epidemic transmission mechanism, a continuous-time Markov process is established to explore the dynamic influence of information dissemination behavior and observation behavior on market demand. The research shows that when the total dissemination duration is sufficiently long, an increase in the information dissemination rate can accelerate the speed of demand diffusion, but has no effect on the final purchase scale. Under different total dissemination durations, the information dissemination rate can affect the diffusion scale only within a certain range, and this range is related to the total duration—the longer the total duration, the smaller the effective range. This finding indicates that when considering marketing strategies targeting new users, extending the marketing duration within a certain range is effective; however, for improving the stickiness and loyalty of existing users, extending the promotion duration has little effect.

Leveraging online social platforms to establish brand promotion bases. To effectively enhance the market influence of airline ticket products, airlines and online travel agencies need to actively engage in strategic collaborations with social media platforms to build brand promotion bases. The communication effectiveness of airline ticket brands and products on social media directly influences users' travel choices and purchase intentions. Selecting influential social media platforms for promotional guidance can effectively expand market scale, increase route sales shares, and hold significant strategic importance for the sustainable development of airlines and ticketing platforms. In an era where social media has become a mainstream communication channel, online social media possess coverage and user guidance capabilities that traditional media cannot match. Strategic cooperation between airlines and social media platforms helps leverage the information reach and user community advantages of social media to accelerate product promotion, reduce marketing costs, and enhance communication effectiveness in aspects such as flight information awareness, fare value

ISSN: 2692-7608 DOI: 10.6981/FEM.202605_7(5).0010

perception, and route word-of-mouth, thereby fully tapping potential travelers and expanding the travel demand market.

## Acknowledgments

The authors gratefully acknowledge the financial support from my tutor.

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