Journal of Organizational and End User Computing
Volume 35 • Issue 3

How Long Will It Delay?
An Empirical Study on Iterative Growth of Internet Word-of-Mouth (IWOM)

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ABSTRACT

In the growth process of movie IWOM, the antecedent IWOM has a significant influence on the subsequent IWOM. IWOM does not form all at once, but iteratively over a short period. This article explores the influence of IWOM publishers on IWOM growth and the dynamic impact of IWOM on movie box office by using vector autoregressive model (VAR model) and impulse response analysis. The findings reveal that highly influential and active users' statements stimulate discussion enthusiasm and increase related topic discussions. These statements also reduce the discreteness of IWOM. On the other hand, highly professional users make IWOM more discreet. Both increased discussion enthusiasm and differentiated IWOM contribute to the growth of movie box office. Additionally, during the growth of IWOM, there is an approximately five day "advance period of word-of-mouth regeneration": it takes audiences about three days from reading movie reviews to watching a movie, followed by about two days to write their own reviews, and the whole process takes about five days.

KEYWORDS

Internet Word-of-Mouth, IWOM Publishers, Movies, Word-of-Mouth Growth, Word-of-Mouth Iteration

INTRODUCTION

Film markets worldwide are rebounding and showing positive growth after the impact of the pandemic. Gower Street Analytics forecasts the global box office to reach $32 billion in 2023, marking a 23% increase from 2022. China is expected to contribute $6.8 billion to this total. While numerous movies are released worldwide each year, not all of them achieve success. For example, only three to four out of every ten Hollywood blockbusters are profitable (Vogel, 2014). As the film industry continues to grow, finding ways to generate profits from film investment remains a challenging task. Understanding how to improve box office revenue is crucial for film practitioners. The rise of numerous movie review

DOI: 10.4018/JOEUC.327357
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websites has provided a platform for movie fans to freely share their thoughts, making the role of internet word-of-mouth (IWOM) increasingly significant in the industry. Consumers highly value their movie-watching experience, as it requires considerable time, money, and energy. To minimize risks, they rely on third-party word-of-mouth platforms to gather information about movies and make informed decisions.

Unlike IWOM of other products, IWOM of the movie industry has the following three characteristics. Firstly, due to the short life cycle of movies and the emphasis on timeliness, IWOM undergoes dynamic iterations before and after movie releases. People tend to discuss the movie after watching it, and the intensity of IWOM decreases over time (Dellarocas et al., 2007). For instance, a study by Liu (2006) analyzing forty movies found that word-of-mouth was most active during pre-release and premiere weeks, gradually declining thereafter. Moreover, word-of-mouth tends to have a lagged influence, as the growth of subsequent word-of-mouth is shaped by preceding word-of-mouth (Guo & Zhou, 2016). Secondly, the film industry has specialized film critics. They provide consumers and producers with criteria to identify good and bad films by virtue of their high levels of knowledge and professional skills in film aesthetics (Corciolani et al., 2020; Hsu, 2006). These specialized critics serve as valuable resources for both consumers and producers, providing guidance in movie selection and contributing to the marketing of movies. Thirdly, specialized critics in the movie industry often focus their IWOM on various aspects of the movie, including stars, directors, aesthetics, and overall assessment (Boatwright et al., 2007), but often do not involve movie details or spoilers, leaving some room for imagination.

Overall, existing research has mainly focused on IWOM information characteristics like IWOM number and valence, but few studies have explored their dynamics changes (Gelper et al., 2018). How antecedent word-of-mouth is acting on postecedent word-of-mouth and how IWOM dynamically affects box office revenues are not sufficiently studied. Moreover, the research on how IWOM publishers affect the growth of IWOM is insufficient. Therefore, it is necessary to conduct a time series study on IWOM and provide management suggestions for enterprises to formulate appropriate marketing strategies according to the changing characteristics of IWOM in different periods. This study focuses on the role of IWOM publishers in the iterative process of IWOM growth and explores the following three related questions by building a time series model: (1) What is the impact of IWOM publishers on IWOM growth and iteration? (2) How does the iterative growth of IWOM affect the box office of movies under the role of IWOM publishers? (3) Do the above effects have different lags?

The Chinese Spring Festival season (New Year's Eve to the sixth day of the first lunar month) is a seven-day period of concentrated cinema screenings in China. This season holds significant importance, contributing to 16.5% of the total national box office in 2021 and 20% in 2022. During the 2021 Spring Festival season in China, *Hello, Lee Hwan-young* achieved tremendous success, grossing $822 million worldwide, largely driven by the Chinese movie market. Douban.com, China's largest film community sharing site with over 200 million users, serves as an important platform to express the opinions regarding films. This study utilized Python to collect comments and related information from Douban.com within thirty days of the film's release. Employing a vector autoregressive (VAR) model, the study aimed to explore the interaction mechanism between IWOM publishers, IWOM, and movie theater revenue.

LITERATURE REVIEW

Research on Film Reviews and IWOM Publishers

The widespread availability of the internet allows consumers to easily access and utilize various types of IWOM information, such as online user reviews and professional reviews (Zhou & Duan, 2016). Online user reviews are generated by online general consumers to share their experiences, such as book reviews on Amazon, software reviews on CNETD, etc. Professional reviews are provided by experts with a certain level of expertise and appreciation to attest to the quality of a product, such as the reviews that movies often receive before their release, and professional reviews of selected products on Amazon and CNETD (Haan et al., 2005). Since the 1940s, film criticism has been a profession (Zhang & Dellarocas, 2006), and those who do so are known as professional film critics. Film IWOM publishers can be broadly divided into two types: professional critics and ordinary consumers. Reviews by professional critics and ordinary users can influence sales in different ways (Deng, 2020).

Pang et al. (2022) point out that professional film critics can be considered as opinion leaders in the dissemination of film information. They legitimize their role as opinion leaders by demonstrating expertise and associated elite tastes. Professional film critics play a crucial role in the film industry and their reviews can generate public attention. Consumers often refer to their professional opinions when making decisions about watching films (Currid, 2007). While many studies have examined the influence of word-of-mouth publishers on movie box office, fewer have focused on the impact of word-of-mouth publishers on the iterative process of IWOM growth.

From the perspective of user characteristics, scholars have selected statistical indicators such as the number of posts, followers, replies, and retweets to evaluate the influence, activeness, and professional authority of opinion leaders (Cha et al., 2010; Chai et al., 2023; Liu et al., 2019). This study expands upon the work of Cha et al. (2010) and Liu et al. (2019) in measuring opinion leaders in the film industry (influence, activeness) and adding the specialization dimension based on the researches of Ryu and Han (2021) and Du et al. (2021). In brief, this paper measures the influence of film IWOM publishers (including professional film critics and general consumers) on IWOM and box office from their influence, activeness, and specialization.

Research on Dynamic IWOM

Word-of-mouth behavior can be manifested as antecedent word-of-mouth and postecedent word-of-mouth (Guo & Zhou, 2016; Moliner-Velázquez et al., 2021). Consumers tend to refer to existing word-of-mouth information before purchase to reduce risk (Flanagin et al., 2014), and they may review and spread it after purchase for certain motives (Laughlin & MacDonald, 2010), which promotes the dynamic iterative growth of word-of-mouth. There are contradictions in the empirical results of the relationship between pre-word-of-mouth and post-word-of-mouth in previous studies. For example, Ma et al. (2013) showed that front word-of-mouth rating positively influenced back word-of-mouth rating, while Wang et al. (2018) thought that there was a negative correlation between them. There is still room for exploration on how front word-of-mouth affects back word-of-mouth.

On the research of IWOM in the field of marketing, scholars mainly discuss it from two perspectives: individual level and market level, focusing on the publisher's motivation, receiver's response, and the role of IWOM in the company's market performance. For example, Kreis and Gottschalk (2015) believed that three motivations of content satisfaction, social satisfaction, and process satisfaction influence IWOM posting behavior. Bronner and Hoog (2011) proposed that IWOM would be influenced by self-orientation and social interest motivation. Casaló et al. (2015) found that online hotel ratings were related to consumers' attitudes toward hotels and booking intentions and both of them would be improved if hotels stay ahead of others in the hotel rankings.

In the context of IWOM and performance, Yazdani et al. (2018) found that reviews from top and bottom ranked reviewers have differing impacts on product sales, with the latter having a greater influence. Some scholars have also considered the dynamics of IWOM. Elberse and Eliashberg (2003) investigated the relationship between IWOM and movie box office at different stages, dividing it into the opening week and the remaining weeks. Liu (2006) highlighted the evolving nature of IWOM reviews, which start before a movie is released and continue throughout its screening period. For products with short life cycles such as movies and video games, the impact of IWOM on performance decreases over time. Li et al. (2022) discovered that the box office revenue reaches its peak during the initial stage of the film, and then decreases exponentially with time. Gelper et al. (2018) observed the peak of IWOM occurring around product releases, including movies, books, videos, and music. By constructing a time series model, he concluded that the peak of pre-sale word-of-mouth was positively correlated with box office performance on the opening weekend. Differently, Cadario (2015) focused on products with longer life cycles and analyzed the dynamic impact between IWOM and TV show ratings. He proposed that with the passage of time, there was an inverted U-shaped relationship between them, and that enterprises need to adjust their online marketing strategies according to different product life cycles.

Some studies have noted the dynamics of IWOM and discussed the dynamic impact of IWOM on sales revenue. However, few of these studies have explored the dynamic iterative growth of word-of-mouth itself. IWOM can be measured by indicators such as IWOM number, IWOM valence, and IWOM dispersion (Chiu et al., 2022; Li et al., 2016). Focusing on the film industry, this study also uses these three indicators to measure IWOM and examine the effect of antecedent IWOM on postecedent IWOM and the dynamic mechanism of IWOM on box office revenue.

THEORETICAL ANALYSIS

The Impact of IWOM Publishers on IWOM

IWOM publishers, including professional film critics and ordinary consumers, have the ability to influence other consumers' behavior. Ryu and Han (2021) mentioned that influential people share their ideas and opinions with consumers through online social networking, interact with others, and make additional feedback and comments. They can spread information with their viral transmission ability to maximize the overall reach of the message. In online communities, opinion leaders tend to possess greater influence and can shape the behavior of others (Chai et al., 2023). Many scholars have found a strong correlation between influencers' characteristics and IWOM (Delafrooz et al., 2019; Serranno & Ramjaun, 2018; Yuan et al., 2022). Reviews, as an important form of IWOM, serve two purposes: increasing consumer awareness and persuasively changing their original beliefs about a product (Pei & Mayzlin, 2022). The improvement of the influence of word-of-mouth publishers may enhance the popularity of movies and the number of word-of-mouth discussions. Moreover, the interpersonal communication of opinion leaders, such as professional film critics, as intermediaries, tends to be more persuasive than direct communication, leading to converging word-of-mouth and reduced dispersion. Based on these insights, this study proposes the following hypotheses:

H1a: There is a positive impact of IWOM publishers' influence on the number of IWOM.
H1b: The influence of IWOM publishers has a negative impact on the dispersion of IWOM.

User activeness refers to the frequency of interactive behaviors such as posting, commenting, and liking by a user in an online community. Both regular users and opinion leaders invest significant time participating in discussions and commenting to maintain their influence (Lee & Eastin, 2020). Users with high activeness have a greater likelihood of gaining attention and influencing online opinions, thereby impacting the growth of IWOM. Opinion leaders' posts generate more discussion and increase event visibility (Wu et al., 2020). The increased activeness of IWOM posters may lead to more movie discussions and an increase in word-of-mouth volume. Moreover, highly active opinion leaders tend to have more persuasive communication, which can contribute to greater consistency in movie word-of-mouth and reduced dispersion. Based on these findings, this study proposes the following hypotheses:

H2a: There is a positive impact of IWOM publishers' activeness on the number of IWOM.
H2b: IWOM publishers' activeness has a negative impact on IWOM dispersion.

Opinion leaders actively engage in experiencing, participating, commenting, and acquiring knowledge in relevant fields to enhance their expertise and maintain their influence. Higher product involvement is a key characteristic of opinion leaders' professionalization. Social media influencers, as topic-specific opinion leaders, possess experience and insights that positively influence followers' trust (De Veirman et al., 2017; Hassan et al., 2021; Singh et al., 2020), which makes it easier to accept the views of influencers. The improvement of the specialization of word-of-mouth publishers may lead to the improvement of the credibility of their word-of-mouth. At the same time, the dissemination of more professional opinion leaders may be more persuasive, potentially leading to a consistent and less discrete word-of-mouth for films. Accordingly, this paper makes the following hypotheses:

H3: There is a negative impact of IWOM publishers' specialization on IWOM dispersion.

The valence of a review indicates the favorability of the product and can be determined by calculating the mean of all reviewers' ratings. The correlation between box office and total positive reviews found in the existing literature may be due to a third factor, namely the quality of the movie. Therefore, the relationship between IWOM publishers' characteristics and IWOM valence will not be examined in the study.

The Impact of IWOM on Movie Box Office

Many scholars have studied the relationship between IWOM and purchase behavior. In terms of entertainment products, IWOM has a positive effect on book sales (Chevalier & Mayzlin, 2006), TV ratings (Bae & Kim, 2021), and movie box office revenues (Chintagunta et al., 2010). When consumers receive information that helps them to make decisions, if their participation is low or their information processing ability is poor, they will more care about the quantity of information (Gupta & Harris, 2010). Both Kaushik et al. (2018) and Liu 2016) found a positive correlation between the number of online reviews and consumers' purchase behavior. The higher the quantity of word-of-mouth, the higher the product buzz, indicating that more people are involved in the discussion of the product, which helps to increase the "exposure" of the product, and then trigger the awareness effect of the number of IWOM, leading to higher sales (Bae & Kim, 2019). Online reviews of movies gave birth to IWOM, which greatly influence consumers' attitudes and purchase decisions (Peng, 2021). Pang et al. (2015) found that after controlling for the expert review effect, both the number and valence of IWOM have a significant positive relationship with the performance of movie box office. Accordingly, this paper makes the following assumptions:

H4: The number of IWOM has a positive impact on box office.

Word-of-mouth valence, reflecting whether opinions are positive or negative, is a critical dimension of word-of-mouth (Liu, 2006), and is critical to consumer purchase decisions (Keyzer et al., 2017). Several studies have demonstrated the positive impact of word-of-mouth valence on decision-making behavior. For instance, Bae and Kim (2021) found that social media valence positively influences episode ratings. Chintagunta et al. (2010) analyzed box office sales data and online review data, highlighting the significant positive effect of word-of-mouth valence on box office revenues. However, some scholars argue that the relationship between word-of-mouth valence and decision-making behavior is not absolute. For example, Duan et al. (2008) found no significant association between word-of-mouth valence and movie box office, suggesting that the quantity of word-of-mouth has a greater influence. Similarly, Kim et al. (2013) found no direct positive relationship between word-of-mouth valence and box office revenue. Therefore, the relationship between word-of-mouth valence and decision-making behavior still needs to be further verified. Nonetheless, this study concludes that word-of-mouth ratings can moderately influence audiences' movie-watching intentions. Accordingly, this paper makes the following hypotheses:

H5: IWOM valence has a positive impact on box office.

Word-of-mouth dispersion effectively reflects the extent of inconsistency and diversity in opinions. However, research on the relationship between IWOM dispersion and purchase behavior yields conflicting results. Zhang et al. (2011) found a positive predictive effect of IWOM dispersion on average weekly movie box office revenue using blog data. Clement et al. (2007) demonstrated that highly discrepant reviews positively influence book success by increasing awareness and promoting sales. Clemons et al. (2006), found a positive relationship between ratings dispersion and sales growth for beer products. In contrast, He and Bond (2015) revealed a negative effect of word-of-mouth dispersion on consumers' purchase intention. Xie et al. (2018) proposed that word-of-mouth dispersion may increase perceived risk, negatively impacting consumption intention. Given the varying effects across industries, further exploration of the impact of word-of-mouth dispersion on sales revenue is needed. This study proposes that high levels of discrepant word-of-mouth can stimulate discussion enthusiasm and contribute to the increased popularity of movies, resulting in a positive impact on movie box office performance. Based on these considerations, the following hypotheses are proposed:

H6: The dispersion of IWOM has a positive impact on box office.

RESEARCH DESIGN

Research Purpose and Model Selection

This paper aims to develop a dynamic model to explore the relationships between IWOM publishers' influence (Influ), activeness (Act), specialization (Spec), number of IWOM (Num), valence of IWOM (Mean), dispersion of IWOM (Std), and movie box office performance (Box). The study focuses on understanding the dynamic correlations among these variables and their impact on IWOM growth and movie box office success. Using data from the film *Hello, Lee Hwan-young* within a thirty-day period after its release, the paper employs a VAR model for time series analysis. This model enables the examination of dynamic interactions between variables at different time lags and assesses the contribution of each variable to the perturbation of dependent variables. By analyzing impulse response functions and variance decomposition, the paper provides valuable insights into the dynamic correlations among these variables.

Variable Setting

Influence of IWOM Publishers: Influ

The number of fans is the total number of a user's followers and is generally used to measure a user's popularity (De Veirman et al., 2017). This paper believes that the number of fans is the most important factor to measure user influence, so the number of fans is selected as an indicator to measure user influence, which is called Influ.

Activeness of IWOM Publishers: Act

User activeness refers to the frequency of a user's interactive behaviors such as posting, commenting, and liking in an online community. In this paper, the ratio of the total number of a user's film reviews and their registration time (rounded up in years) is used to measure this activeness, which is recorded as Act. The larger the ratio is, the more film reviews the user posts per year after registration, and the more active the user is.

Specialization of IWOM Publishers: Spec

In this study, the specialization of IWOM publishers (denoted as Spec) is measured by analyzing the total count of books read and movies watched, which are displayed on their user profile pages on Douban.com. A higher count indicates a greater level of specialization and expertise.

Number of IWOM: Num

In this paper, the number of IWOM refers to the quantity of movie reviews posted by viewers on internet platforms. Since online film reviews are the primary form of IWOM for movies, the number of online film reviews is used as a metric to measure the volume of word-of-mouth, denoted as Num.

Valence of IWOM: Mean

Word-of-mouth valence refers to the word-of-mouth spreader's score on word-of-mouth, which is an important indicator to quantify the word-of-mouth spreader's liking for products. In this paper, the average value of effective online scores was selected as the measurement unit of word-of-mouth valence to measure its influence, denoted as Mean.

Dispersion of IWOM: Std

Word-of-mouth dispersion refers to the degree of praise or criticism of a product, which is generally measured by word-of-mouth standard deviation, variance, or coefficient of variation. In this paper, the standard deviation of effective online scores was selected as the measurement unit of word-of-mouth dispersion to measure the influence of word-of-mouth dispersion, denoted as Std.

Box Office: Box

It is objective and reasonable to measure consumers' willingness to watch movies by using the box office data and to reflect their willingness to watch movies through the sales data. In this paper, the total box office data of the film in some days before its release is selected and denoted as Box.

The definitions of each variable will be shown in Table 1.

Sample Selection and Data Sources

Using Python, this study collected a total of 7,850 comments and related information on the movie *Hello, Lee Hwan-young* within thirty days of its release. The dataset was carefully filtered to exclude

Table 1. Variable definition

Variable type	Variable name	Variable symbol	Variable definition
Independent variable	Influence	*Influ*	Number of fans
	Activeness	*Act*	The ratio of the total number of posts posted by users to the number of years they registered (rounded up by year)
	Specialization	*Spec*	The number of books the publisher has read and the number of films they has seen
Independent variable	Number of word-of-mouth	*Num*	Number of network ratings
	Valence of word-of-mouth	*Mean*	Average network scores
	Dispersion of word-of-mouth	*Std*	Network scores variance
Dependent variable	Movie box office	*Box*	Cumulative theatrical revenue of a film

Note: All variables were analyzed by vector autoregression after the logarithm was taken any incomplete data. The information processed included review text, user rating, publisher ID, registration duration, number of fans, number of posts, number of books read, and number of movies watched. These variables were used to derive the IWOM publisher's influence (Influ), activeness (Act), specialization (Spec), number of IWOM (Num), valence (Mean), and dispersion (Std). To ensure data stability and mitigate potential heteroscedasticity, the natural logarithm (lnX) was applied to all variables. Descriptive statistics for all variables were obtained using STATA software and are presented in Table 2.

Based on the data collected, the film's box office reached 5.231 billion on the thirtieth day, making it one of the highest-grossing films in China's history. Over time, both the number and dispersion of word-of-mouth increased, while the average movie rating (word-of-mouth valence) showed a gradual decrease. In terms of word-of-mouth publishers, all three indicators (influence, activeness, and specialization) displayed continuous growth. With the indicators established, the study will proceed with empirical analysis.

EMPIRICAL ANALYSIS

Stability Test

This study used the ADF unit root test to test the stability. The results are shown in Table 3.

According to the result of the test, the ADF values of all time series are lower than -3.723, and at the significant level of 0.05, all of them reject the original hypothesis of the existence of unit roots. That is, lnBox, lnNum, lnStd, lnMean, lnFlu, lnAct, and lnSpec all have good stability, which meets the conditions of model construction and granger causality test, avoiding the phenomenon of spurious regression.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Box	30	400512.0000	147100.7000	29145.5000	523036.4000
Num	30	3703.2330	1423.9910	127.0000	4883.0000
Mean	30	4.0734	0.2673	3.2432	4.2252
Std	30	1.0661	0.1492	0.9739	1.4905
Act	30	12023.5700	4138.1590	945.5326	15307.3600
Influ	30	1195890.0000	47031.1800	999864.0000	1231887.0000
Spec	30	855912.4000	258217.7000	125018.0000	1075142.0000

Table 3. ADF unit root test

Variable name	Differential order	ADF statistics	P value	Stability
lnBox	0	-71.660	0.0000	stable
lnNum	0	-25.802	0.0000	stable
lnStd	0	-4.055	0.0011	stable
lnMean	0	-4.320	0.0004	stable
lnFlu	0	-14.351	0.0000	stable
lnAct	0	-20.602	0.0000	stable
lnSpec	0	-19.685	0.0000	stable

Determining the Optimal Lag Order and Building a VAR Model

To determine the best lag period of the VAR model and identify the time interval when variables have the greatest mutual influence, this paper selected six conventional statistics, LL, LR, FPE, AIC, HQIC, and SBIC for reference, and the results are shown in Table 4.

The results show that there are five * marks in the lag period two, which means that five of the six statistics which lag two periods have reached the optimum, so two-period lag is the best time interval. Based on this result, this study constructs the VAR model with two lags.

Granger Causality Test

Granger causality test can be used to judge whether there is causality between variables, and its test result is an important basic condition for constructing impulse response function. If the variable X can't Granger cause variable Y, it means that the variable X is exogenous in Y. Granger causality test results between variables obtained by STATA statistical analysis software are shown in the following Table 5.

It can be seen that at the significant level of 0.05, most of the relationships between variables reject the original hypothesis, namely Granger causality. It means that there are a large number of single causal relationships between variables, and these variables can be used to construct the VAR model, which will ensure a certain predictive ability.

Model Stability Test

Unit Root Test

Because this study is going to construct the VAR model of this study for the stationary time series data, to ensure the convergence of the image of the impulse response function, it is necessary to check

Table 4. Determine the statistics of the optimal lag period

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	610.081				4.60E-28	-43.0772	-42.9754	-42.7441
1	944.895	669.63	49	0.000	7.00E-37	-63.4925	-62.678	-60.8281
2	1080.57	271.35*	49	0.000	3.1E-39*	-69.6837*	-68.1564*	-64.6879*

Table 5. Granger causality test (part)

Equation	Excluded	chi2	df	Prob>chi2
lnBox	lnNum	7.188	2	*0.027*
	lnMean	3.4365	2	0.179
	lnStd	9.9827	2	*0.007*
	lnAct	4.9268	2	0.085
	lnInflu	4.6015	2	0.100
	lnSpec	10.778	2	*0.005*
	ALL	202.08	12	*0.000*
lnNum	lnAct	1.0612	2	0.588
	lnInflu	14.593	2	*0.001*
lnStd	lnAct	28.76	2	*0.000*
	lnInflu	38.092	2	*0.000*
	lnSpec	6.8703	2	*0.032*

the stability of the VAR model. Figure 1 shows that the characteristic roots are all located within the unit circle, indicating that the model is stable and the modeling is successful.

Cointegration Test

This study uses the Johanson test method to test all variables by cointegration. The purpose is to judge whether there are significant economic fluctuations between time series or short-term deviations from the mean due to seasonal factors. In this way, this study can analyze whether there is a long-term balanced and stable relationship among variables. The results of the cointegration test are shown in Table 6. The results show that the VAR model constructed in this study has at most five cointegration relationships, and there is a long-term stable relationship among variables.

Figure 1. Unit root test

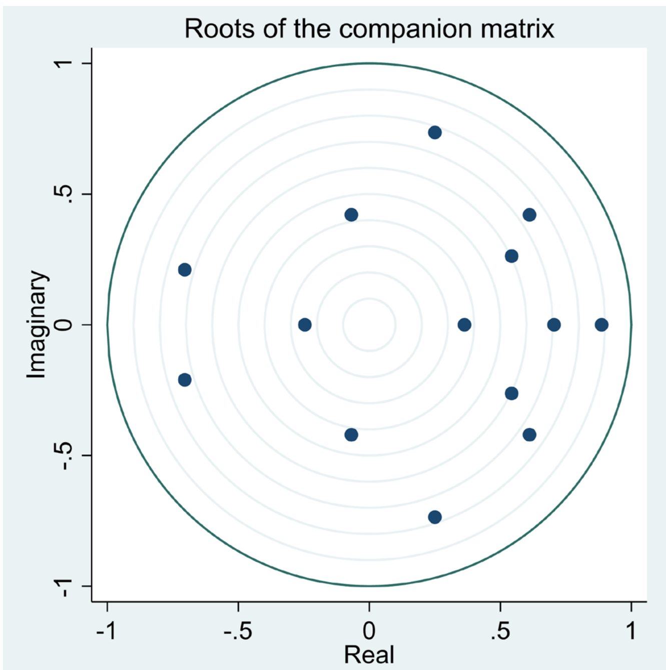


Table 6. Cointegration test

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	7	551.18		832.1923	124.24
1	20	704.25	0.99997	526.0519	94.15
2	31	813.16	0.99945	308.2210	68.52
3	40	906.45	0.99839	121.6378	47.21
4	47	942.89	0.91899	48.7553	29.68
5	52	961.95	0.73125	10.6505*	15.41
6	55	965.25	0.20364	4.0470	3.76
7	56	967.27	0.13025		

Note: Number of obs = 29, Lags=1

Impulse Response Analysis

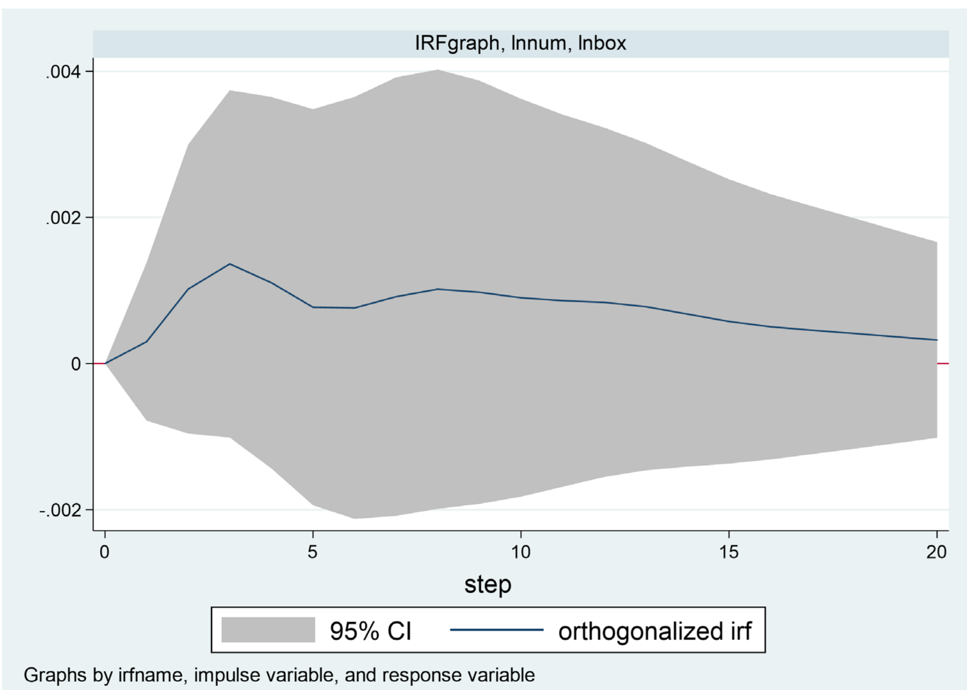
Impulse response analysis is based on the impulse response function to test the influence of random disturbance terms and it can explore the interaction among variables. The image of the impulse response function can intuitively show how the random disturbance term affects other variables in different periods, which is consistent with the research goal of this study. Based on the above, impulse response analysis can be seen as the core of this study.

Impulse Response Analysis of the Number of Word-of-Mouth (Num) to the Movie Box Office (Box)

According to Figure 2, the movie box office does not immediately respond to a unit standard deviation increase in the word-of-mouth number. However, from the second period onwards, the number of word-of-mouth has a consistently positive impact on the movie box office, which lasts until at least the twentieth period. After the eighth period, the impact effect becomes small, almost negligible. The third period exhibits the peak positive impact effect, followed by a downward trend. Within this overall downward trend, a small peak appears between the seventh and eighth periods. These empirical analysis results are consistent with hypothesis H4.

The findings indicate that an increase in the word-of-mouth number can enhance a movie's popularity. The awareness generated by the word-of-mouth number increases the movie's online visibility, resulting in a rise in the quantity of word-of-mouth. The positioning of the two positive impact peaks suggests that the movie box office is mainly influenced by word-of-mouth numbers from two to three days ago and seven to eight days ago. This can be attributed to the typical time interval between ticket purchase decisions and movie viewing. Many netizens tend to buy tickets approximately three days in advance, explaining the first peak of positive impact. Additionally, some viewers prefer to purchase tickets a week in advance, leading to the second peak of positive impact.

Figure 2. Impulse response analysis of the number of word-of-mouth (num) to the movie box office (box)



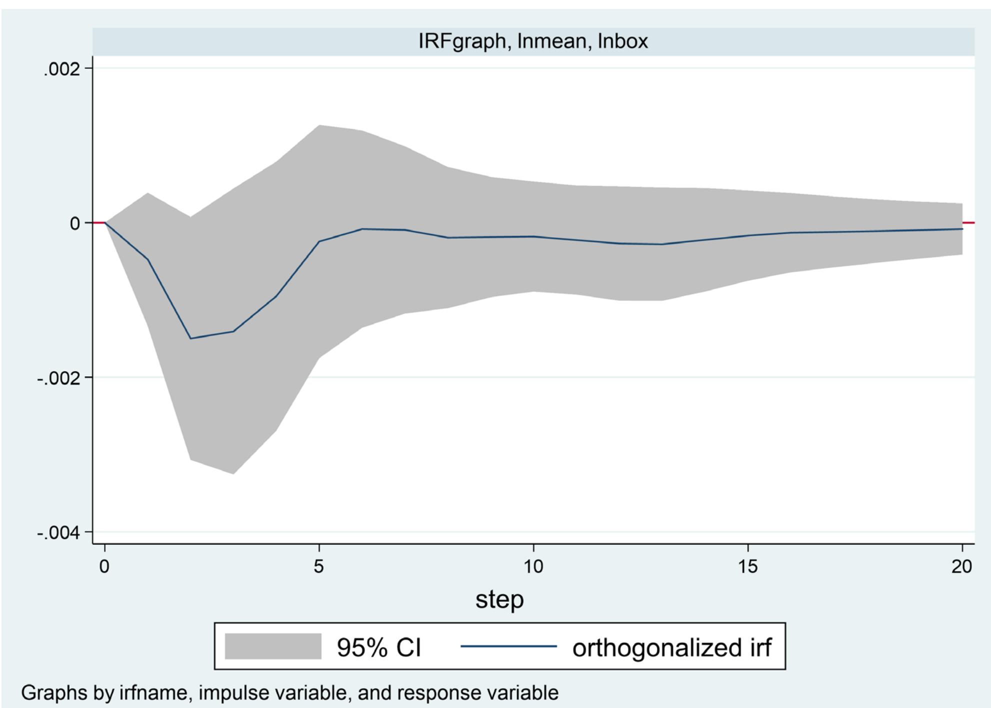
Impulse Response Analysis of Word-of-Mouth Valence (Mean) to Box Office (Box)

Figure 3 indicates that the movie box office does not respond immediately to a unit standard deviation impact of word-of-mouth valence. From the second period onward, word-of-mouth valence negatively affects the movie box office, which persists until at least the twentieth period. However, the impact diminishes after the fifth period, becoming almost negligible. The second period represents the peak of the negative impact, followed by a downward trend. These empirical analysis results contradict hypothesis H5 of the study.

Nevertheless, the research findings regarding the impact of word-of-mouth valence on customers' willingness to watch movies can be reasonably explained. Movies are unique products that contain subjective and experiential content, resulting in varying views among audiences. A movie with positive feedback may not necessarily achieve high box office results. Additionally, according to the double-sided persuasion theory, the presence of negative comments can enhance the credibility of positive comments and stimulate discussions, thereby increasing word-of-mouth volume. Furthermore, high initial ratings can lead to heightened audience expectations, and the decline in surprise factor may contribute to a decrease in ratings. Although the film score for *Hello, Lee Hwan-young* exhibited a slight downward trend after its release, it remained relatively stable and did not experience a significant decline in word-of-mouth. It is important to note that this study only analyzed one film, and further research with a larger dataset is needed to verify the negative impact of word-of-mouth valence, which can serve as an essential starting point for future investigations.

The impulse response function image shows that the influence of IWOM number on box office is more lasting and decays more slowly than that of IWOM valence. For such a kind of products, like movies, the awareness effect brought by the increase in word-of-mouth number often has a greater impact on the box office than the persuasion effect brought by word-of-mouth valence.

Figure 3. Impulse response analysis of word-of-mouth valence (mean) to the movie box office (box)



Impulse Response Analysis of Word-of-Mouth Dispersion (Std) to Box Office

Figure 4 reveals that the movie box office does not respond immediately to a unit standard deviation impact of word-of-mouth dispersion. Starting from the second period, word-of-mouth dispersion exhibits a consistently positive impact on the movie box office. This positive impact persists until at least the twentieth period, with diminishing effects after the eighth period, becoming almost negligible. The third period represents the peak of the positive impact, followed by a downward trend. However, it subsequently experiences an upward phase, with a minor peak in the seventh period. These empirical analysis results align with hypothesis H6.

The findings indicate that increased word-of-mouth dispersion leads to diverse opinions on the internet about a movie. These differences in views spark discussions and more word-of-mouth instances. This creates awareness and increases consumers' interest in watching the movie, resulting in higher box office performance. Analyzing the positions of the two positive impact peaks reveals that an increase in word-of-mouth dispersion enhances consumers' movie-watching willingness. Similar to the influence of word-of-mouth number, movie-watching willingness is primarily influenced by word-of-mouth dispersion from approximately three days ago and seven days ago. These two time intervals represent favored lead times for audiences to purchase movie tickets.

Impulse Response Analysis of Word-of-Mouth Publisher's Influence (Influ) and Activeness (Act) to the Number of Word-of-Mouth (Num)

Figure 5 shows that the number of word-of-mouth instances does not immediately respond to a unit standard deviation impact of influence. However, from the second period onwards, influence consistently has a positive impact on the quantity of word-of-mouth, lasting until at least the twentieth period. The peak of this positive impact occurs in the fifth period, followed by a gradual decline. These findings support hypothesis H1a.

Figure 4. Impulse response analysis of word-of-mouth dispersion (std) to the box office (box)

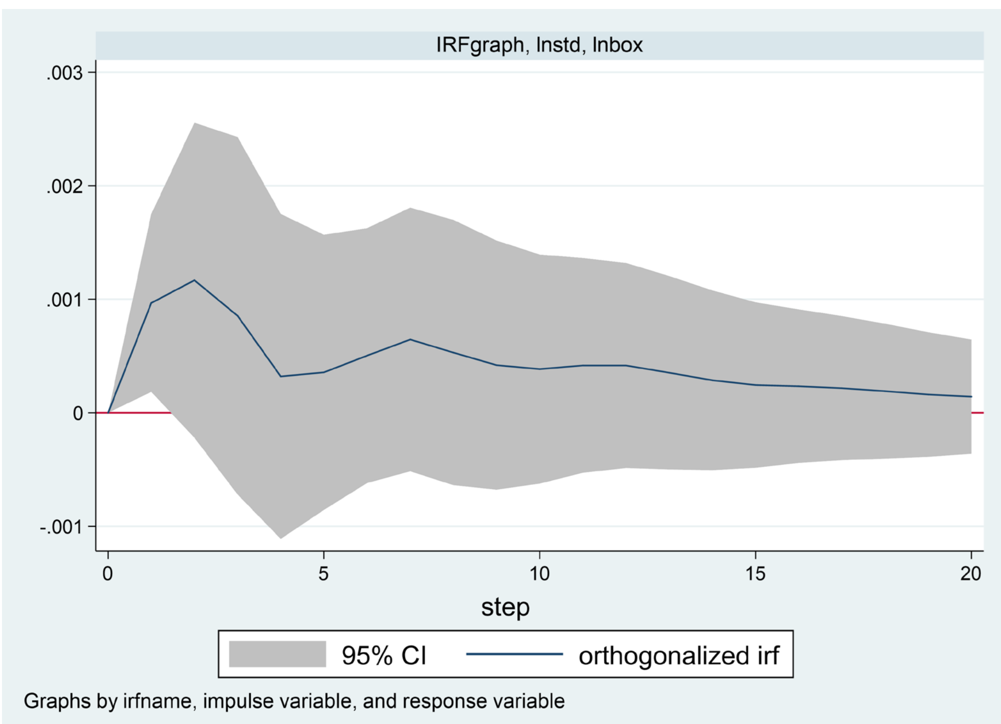
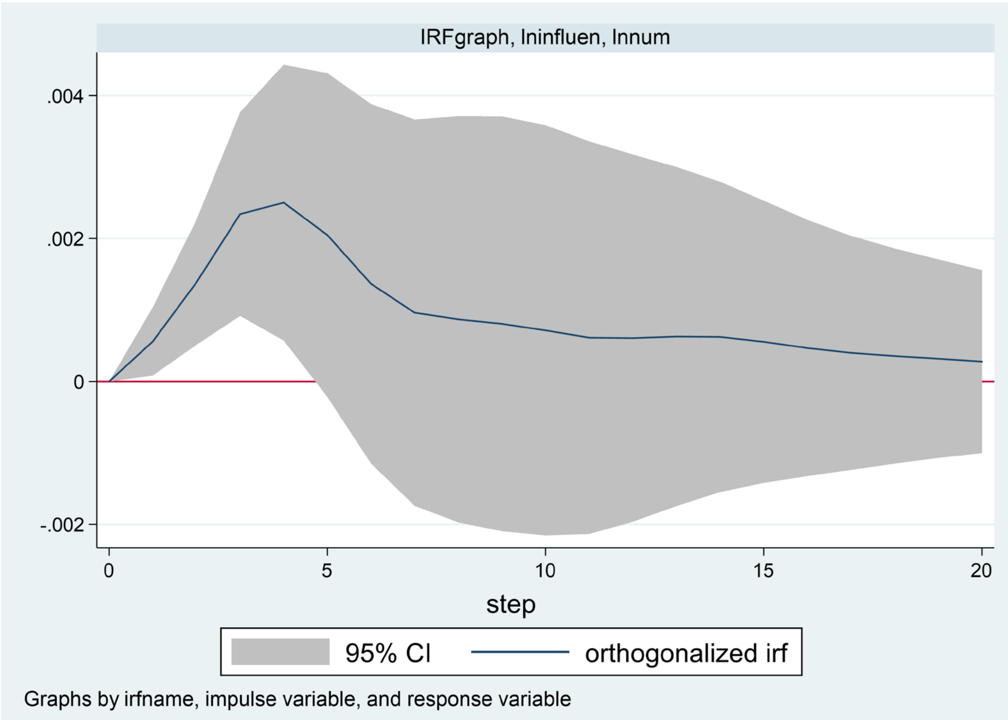


Figure 5. Impulse response analysis of word-of-mouth publisher's influence (influ) to the number of word-of-mouth (num)



The analysis suggests that as the influence of word-of-mouth publishers accumulates, the two-step communication theory comes into play. This theory explains how their fans join discussions, leading to the rapid spread of information about the movie and an increase in word-of-mouth instances. This, in turn, boosts the movie's popularity and triggers the awareness effect of word-of-mouth instances. The peak impact is observed between the fourth and fifth periods, likely due to the time lag between reading film reviews, watching the movie, and subsequently writing comments, which is typically around five days.

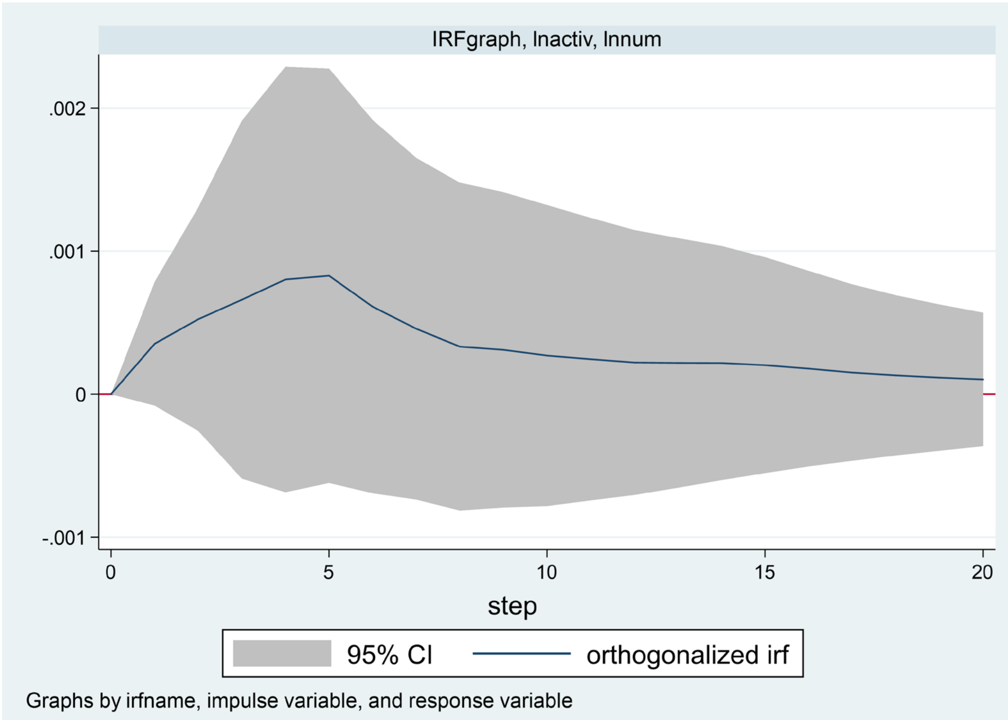
According to Figure 6, the number of word-of-mouth instances does not immediately respond to a unit standard deviation impact of activeness. However, starting from the second period, activeness consistently has a positive impact on the number of word-of-mouth instances, lasting until at least the twentieth period. The peak occurs in the fifth period, followed by a downward trend. These findings support hypothesis H2a.

The increased activeness of word-of-mouth publishers indicates greater user engagement in discussions. Through their frequent interactions, film information spreads rapidly and widely, leading to increased word-of-mouth instances and ultimately boosting the movie's box office performance. The positioning of the peak aligns with previous analysis, confirming the validity of the discussion.

Impulse Response Analysis of Word-of-Mouth Publisher's Influence (Influ), Activeness (Act), and Specialization (Spec) to Word-of-Mouth Dispersion (Std)

According to Figure 7, word-of-mouth dispersion does not immediately respond to a unit standard deviation impact of influence. However, starting from the second period, specialization consistently has a negative impact on word-of-mouth dispersion, lasting until at least the twentieth period. The peak occurs between the third and fourth periods, followed by a gradual decline. These findings support hypothesis H1b.

Figure 6. Impulse response analysis of word-of-mouth publisher's activeness (act) to the number of word-of-mouth (num)



This phenomenon can be attributed to the increasing influence of IWOM publishers. As more opinion leaders emerge, their comments significantly shape the views of other users. Therefore, the subsequent reviews from other users align with the initial word-of-mouth, leading to a reduction in word-of-mouth dispersion over time. The peak of the observed negative impact between the third and fourth periods indicates that the influence of review publishers on word-of-mouth reaches its maximum effect after a delay of approximately three to four days.

This can be explained by two main factors. Firstly, there is a time interval between reading online reviews and writing one's own review. Users need time to form their own opinions based on their actual movie-watching experiences and pre-existing reviews. Secondly, individuals tend to watch movies and write their own reviews a few days after reading others' online comments. It is less common for consumers to read movie reviews on the same day and immediately go to the cinema.

According to Figure 8, word-of-mouth dispersion does not immediately respond to a unit standard deviation impact of activeness. However, starting from the second period, the activeness of word-of-mouth publishers consistently has a negative impact on word-of-mouth dispersion, which lasts until at least the twentieth period. After the tenth period, the impact becomes small, nearly negligible. The peak occurs between the third and fifth periods, followed by a downward trend. These findings support hypothesis H2b.

The increasing participation of highly active users in movie discussions gradually heats up the conversation among netizens. As the discussions progress, stronger opinions gradually persuade weaker ones, resulting in a convergence of IWOM with similar emotional tendencies and a decrease in dispersion. The peak observed between the third and fifth periods indicates that increased activeness has the greatest influence on the dispersion of IWOM approximately four days later. As more people watch the movie and share their comments on film review websites, IWOM grows. This peak aligns

Figure 7. Impulse response analysis of word-of-mouth publisher's influence (influ) to word-of-mouth dispersion (std)

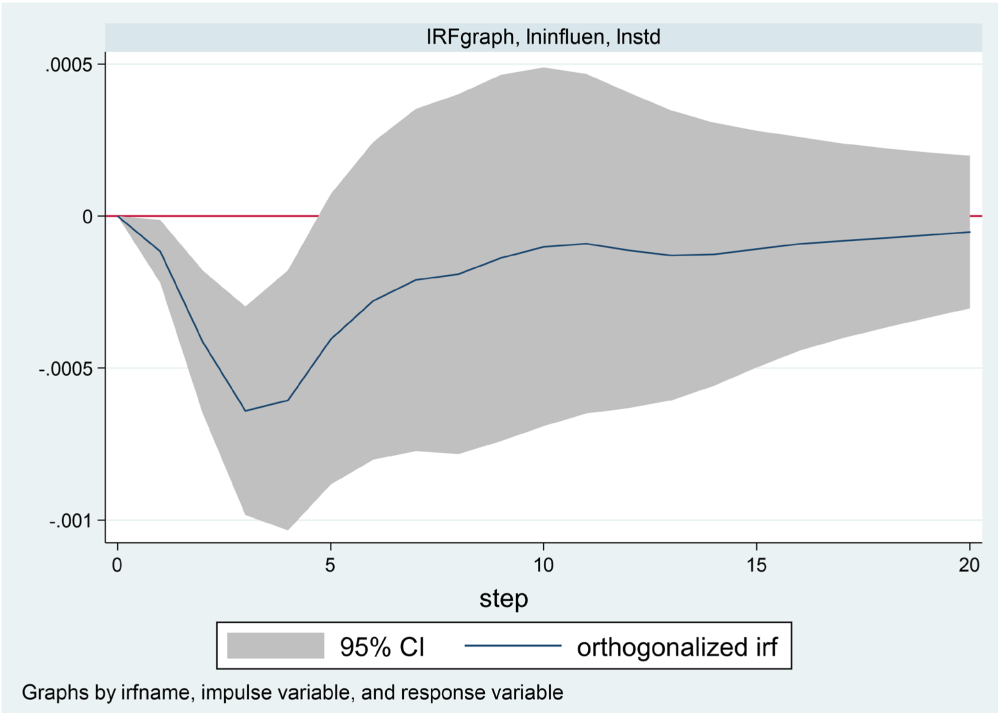
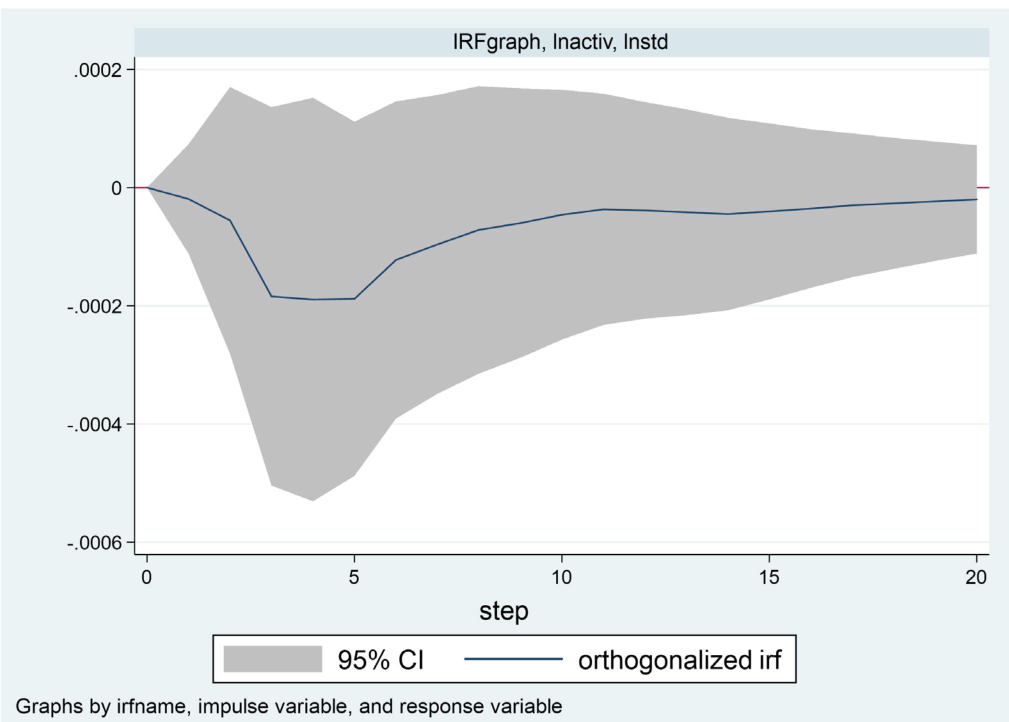


Figure 8. Impulse Response analysis of word-of-mouth publisher's activeness (act) to word-of-mouth dispersion (std)



with the negative impact of increasing influence on IWOM, reaching its highest point around the fourth period.

According to Figure 9, word-of-mouth dispersion does not immediately respond to a unit standard deviation impact of specialization. From the second period, specialization has a continuously positive impact on word-of-mouth dispersion. This effect lasts until at least the twentieth period, but after the tenth period, it becomes minimal. The peak positive impact occurs between the third and fifth periods, followed by a downward trend. These empirical findings contradict hypothesis H3.

The phenomenon can be attributed to the increasing number of professional word-of-mouth publishers whose high-quality opinions carry more persuasive weight. This creates a sense of identification among individuals who share similar views, leading to a consolidation of existing mixed opinions and ultimately an increase in word-of-mouth dispersion.

The research hypotheses and corresponding empirical analysis results are shown in Table 7.

Variance Decomposition

After completing the impulse response function analysis, this study got the effect of each dimension attribute of film critics on IWOM and the influence of IWOM on movie-watching intention. Subsequently, this study used variance decomposition to evaluate the importance and contribution rate of different shocks, and comprehensively analyze the influence of all six shock variables on the movie box office. After integrating the previous research, the results are shown in Table 8.

Among all the factors that influence the movie box office, the box office itself occupies the largest proportion. To explore the proportion of other factors that influence the movie box office, this study removes its influence and remakes the table. Because the data of periods 0~2 account for an extreme proportion, this study selects the variance decomposition data of periods 3~8 to make a line chart. Therefore, we can intuitively see the influence proportion of each variable on the movie box

Figure 9. Impulse response analysis of word-of-mouth publisher's specialization (spec) to word-of-mouth dispersion (std)

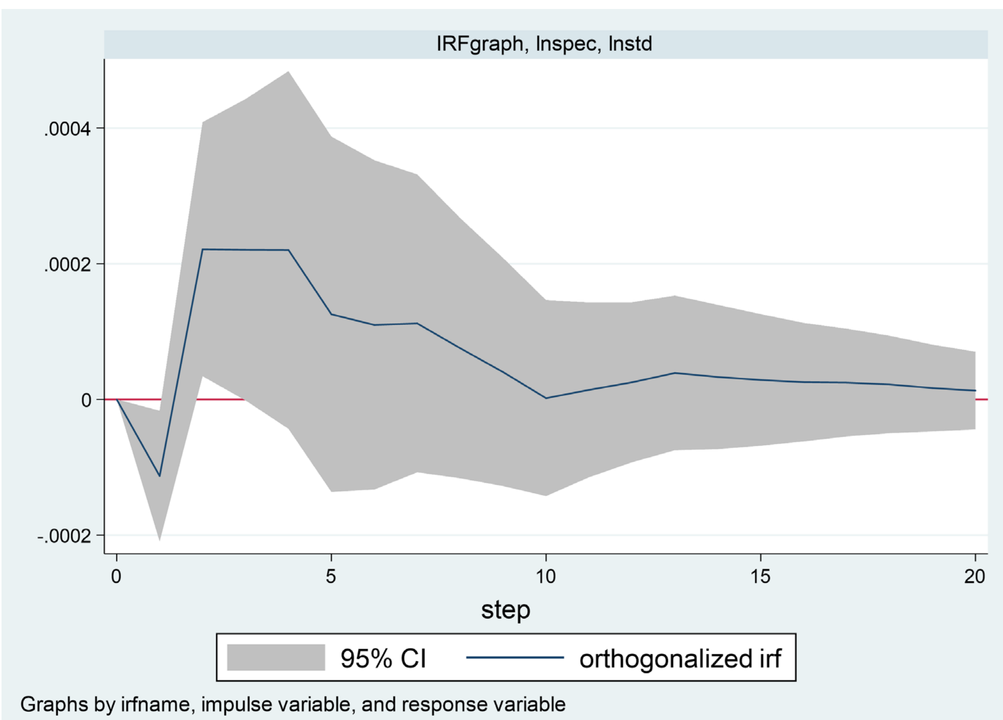


Table 7. Results of hypothesis and empirical analysis (impulse response analysis)

Serial number	Hypothetical content	Empirical analysis results	Is the hypothesis valid?	The peak position of the impulse response
H1a	The publisher's influence has a positive impact on the number of IWOM number (+).	The publisher's influence has a positive impact on the number of IWOM number (+).	yes	5
H1b	Word-of-mouth publisher's influence has a negative impact on the dispersion of IWOM (-)	Word-of-mouth publisher's influence has a negative impact on the dispersion of IWOM (-)	yes	3,4
H2a	Publishers' activeness of word-of-mouth has a positive impact on the number of IWOM (+)	Publishers' activeness of word-of-mouth has a positive impact on the number of IWOM (+)	yes	5
H2b	Publishers' activeness of word-of-mouth has a negative impact on IWOM dispersion (-)	Publishers' activeness of word-of-mouth has a negative impact on IWOM dispersion (-)	yes	4,5
H3	Publishers' specialization has a negative impact on IWOM dispersion (-)	Publishers' specialization has a positive impact on IWOM dispersion (+)	no	4,5
H4	The number of IWOM has a positive impact on movie box office (+)	The number of IWOM has a positive impact on movie box office (+)	yes	3
H5	IWOM valence has a positive impact on movie box office (+)	IWOM valence has a negative impact on movie box office (-)	no	2
H6	Internet word-of-mouth dispersion has a positive impact on movie box office (+)	Internet word-of-mouth dispersion has a positive impact on movie box office (+)	yes	3

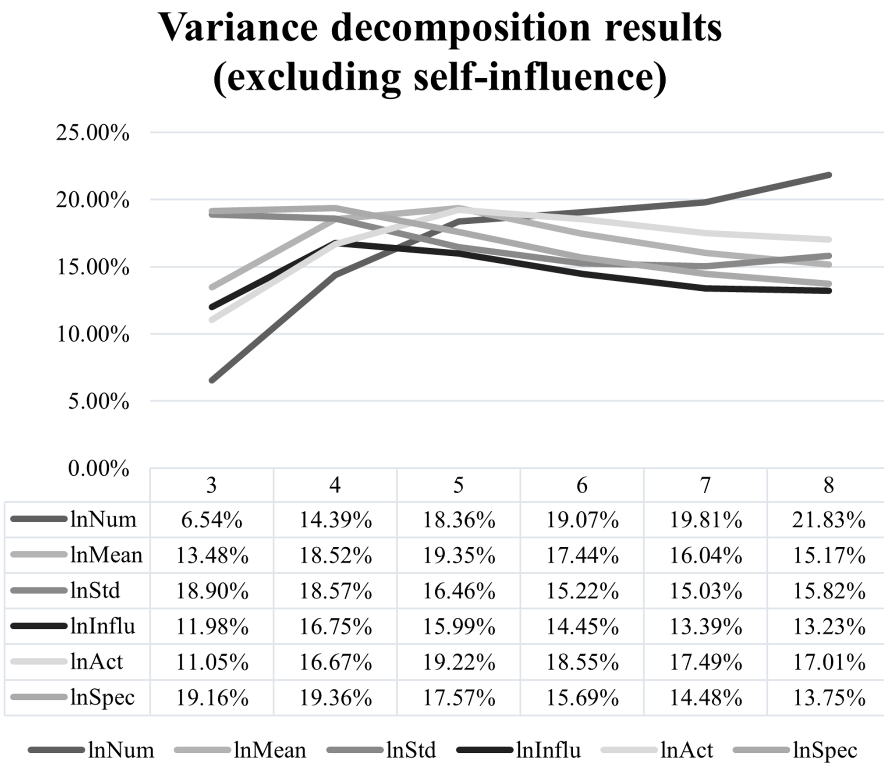
Table 8. Variance decomposition results (No.0 ~ No.8)

Step	lnBox	lnNum	lnMean	lnStd	lnInflu	lnAct	lnSpec
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.9254	0.0016	0.0051	0.0271	0.0158	0.0008	0.0243
3	0.8270	0.0141	0.0326	0.0363	0.0442	0.0081	0.0376
4	0.7764	0.0311	0.0448	0.0357	0.0619	0.0122	0.0380
5	0.7743	0.0397	0.0468	0.0316	0.0591	0.0140	0.0345
6	0.7896	0.0413	0.0422	0.0293	0.0534	0.0135	0.0308
7	0.7988	0.0429	0.0388	0.0289	0.0495	0.0128	0.0284
8	0.7974	0.0472	0.0367	0.0304	0.0489	0.0124	0.0270

office after variance decomposition. The variance decomposition contribution rate of each variable is shown in Figure 10.

According to the chart, during the growth stage of the box office, the proportion of six independent variables is relatively stable and does not fluctuate greatly as time goes on, regardless of their contribution, which indicates that the variance decomposition result is effective. According

Figure 10. Variance decomposition results (excluding self-influence)



	3	4	5	6	7	8
lnNum	6.54%	14.39%	18.36%	19.07%	19.81%	21.83%
lnMean	13.48%	18.52%	19.35%	17.44%	16.04%	15.17%
lnStd	18.90%	18.57%	16.46%	15.22%	15.03%	15.82%
lnInflu	11.98%	16.75%	15.99%	14.45%	13.39%	13.23%
lnAct	11.05%	16.67%	19.22%	18.55%	17.49%	17.01%
lnSpec	19.16%	19.36%	17.57%	15.69%	14.48%	13.75%

to the specific data, the average proportion of variance decomposition contribution of each variable from the third to eighth period is between 14% and 17%, which indicates that the independent variables have a similar degree of influence on the dependent variables, that is, from a comprehensive perspective, word-of-mouth valence, word-of-mouth number, word-of-mouth dispersion, word-of-mouth publisher's specialization, activeness, and influence have similar explanatory power to the change of movie box office. The results of impulse response analysis reflect the impulse response chain from IWOM publishers to IWOM and then to the movie box office. Variance decomposition not only proves mathematically the ability of six explain variables to account for the explained variables but also proves that the selection of models and the set of variables are appropriate.

CONCLUSION AND DISCUSSION

Research Conclusions

This study collected the word-of-mouth data of *Hello, Lee Hwan-young*, which is a popular movie released in the Spring Festival of 2021, from Douban.com to establish a dynamic model consisting of the influence (influ), activeness (Act), and specialization (Spec) of IWOM publishers, the number of word-of-mouth (Num), valence (Mean), dispersion (Std), and box office (Box). This study used the model to explore the dynamic influence of IWOM publishers on the growth of IWOM and the dynamic impact of IWOM on the box office. The research conclusions are as follows.

Firstly, the influence and activeness of IWOM publishers positively affect the number of IWOM, with the greatest impact observed about five days later. This indicates that netizens typically take about five days from reading movie reviews to watching the movie and sharing their own reviews, defining it as the lead time for word-of-mouth regeneration. The increased influence and activeness of IWOM publishers, along with the quantity of discussion about movies, stimulate people's willingness to watch movies, leading to increased popularity and box office revenue.

Secondly, the influence, activeness, and specialization of IWOM publishers impact the dispersion of IWOM. While influence and activeness have a negative impact, specialization has a positive impact. These effects reach their peak around the fourth period, aligning with the five-day "lead time of word-of-mouth regeneration." These findings indicate that IWOM publishers with high influence and activeness can have a wide and frequent impact on other users, influencing subsequent IWOM with a lag time of four to five days. On the other hand, publishers' specialization has the opposite influence on IWOM. Comments from specialized film reviewers with abundant professional knowledge promote diverse discussions, leading to increased IWOM dispersion, film controversy, and ultimately, the promotion of film popularity.

Thirdly, both the number and dispersion of IWOM have positive effects on the movie box office, while the impact of IWOM valence requires further confirmation. Empirical analysis shows that an increase in the quantity and dispersion of IWOM can enhance the popularity of movies, stimulate online discussions, improve movie publicity, and ultimately boost box office revenue. However, the study's empirical analysis also indicates that IWOM valence has a weak negative impact on the movie box office, which differs from previous findings. Further research is needed to modify this conclusion. The peak impact of IWOM on the movie box office occurs primarily on the third day, suggesting that most viewers go to the cinema approximately three days after reading comments.

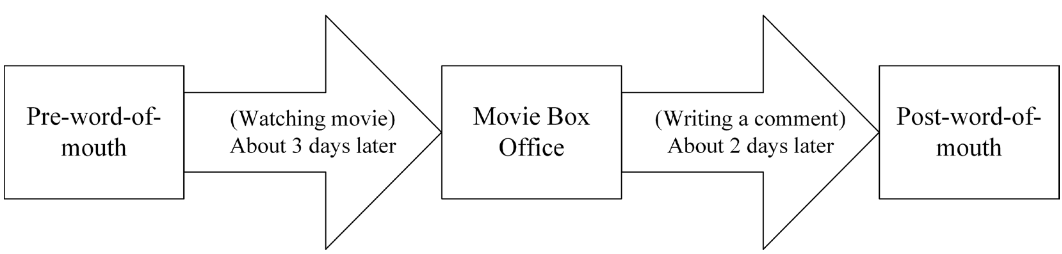
During the growth of IWOM, there is a five-day "lead time of word-of-mouth regeneration." Based on the peak of impulse response mentioned earlier, audiences typically spend around three days reading movie reviews and an additional two days writing their own reviews. This entire process takes approximately five days. Within this timeframe, the audience assesses whether or not to watch the movie based on the overall pre-word-of-mouth. They may also contribute their own reviews, influenced by their personal opinions and the reviews they have read. This dynamic represents a complete cycle of word-of-mouth growth. This study investigates the impact of pre-word-of-mouth on post-word-of-mouth from the perspective of IWOM publishers. Figure 11 provides an illustration of this process.

Research Contributions

This study contributes to the literature in two ways.

Firstly, it addresses the dynamic iteration and growth of internet word-of-mouth (IWOM), filling a research gap in the existing literature. While previous studies have examined the dynamic changes of IWOM and its impact on sales revenue, there has been limited research on how prior IWOM influences subsequent IWOM. To address this gap, this study employs a VAR model to investigate the dynamic time-series of IWOM. The findings reveal a "WOM regeneration lead time" of approximately five days for movie-related IWOM. This innovative application of the VAR model provides a new perspective and deeper understanding of the dynamics of IWOM in the research field.

Figure 11. Iterative diagram of word-of-mouth growth



Secondly, this study explores the dynamic relationships among characteristics of IWOM publishers, IWOM features (number, valence, dispersion), and movie box office performance. While existing research has extensively discussed the relationship between IWOM and sales revenue, particularly regarding the quantity of IWOM, there are discrepancies in the literature regarding the impact of IWOM valence and dispersion on sales revenue. Additionally, research on IWOM dispersion remains relatively scarce. To address these gaps, this study comprehensively examines the influence of IWOM number, valence, and dispersion on movie box office performance, and empirically tests the relationships among these variables. Furthermore, the study emphasizes the characteristics of IWOM publishers and investigates their impact on IWOM during the dynamic growth process. These contributions provide new insights to the research field.

Practical Implications

This research provides practical insights for marketers engaged in internet Word-of-Mouth (IWOM) marketing in the film industry.

Firstly, IWOM marketers can invite highly influential and active users to participate in movie discussions during the film's release phase to enhance its visibility and attract more user engagement. Studies have shown that these influential users' impact on IWOM peaks within four to five days after their participation, and their word-of-mouth further influences subsequent conversations, leading to the growth and iteration of IWOM.

Secondly, IWOM marketers should encourage the formation of diverse IWOM by attracting IWOM publishers with higher expertise to join the discussions. By increasing the dispersion of opinions and evaluations regarding the movie, marketers can enhance the movie's buzz and appeal.

Thirdly, IWOM marketers should monitor the influence of word-of-mouth on subsequent discussions, particularly the impact of word-of-mouth generated four to five days ago. By analyzing these fluctuations, marketers can adjust their strategies promptly. Similarly, when examining box office revenue, they should focus on the IWOM situation from two to three days prior to assess the impact on performance and take timely measures to boost box office success.

Limitations and Further Research

It is important to acknowledge the limitations of this study, which primarily focuses on a single film within the Chinese market. While the findings provide valuable insights, they may not fully represent the diverse range of films or the dynamics of other global film markets. To enhance the generalizability of the conclusions, future research could consider incorporating films from different countries and genres, as well as collecting social media word-of-mouth data from various international sources (Khaletska et al., 2022). Additionally, this paper uses a VAR model to conduct a time-series study of the relationship between IWOM publishers, IWOM, and movie box office. Other factors that may affect the box office, such as movie genre, marketing activities, contemporaneous movie competition, and the influence of directors and actors are not considered in the model. Future studies could include these control variables to provide a more comprehensive understanding of the factors influencing movie success. Machine learning (Fadhli et al., 2022; Gautam & Bansal, 2023) and experimental methods can also be used to improve the study.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

FUNDING

This research was supported by the National Social Science Fund of China (Grant NO.18BGL110).

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