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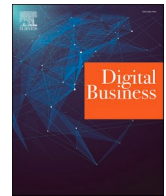
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Sequential film marketing in China: The study of social platforms and their impacts[☆]

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ABSTRACT

Because the Chinese movie market is regarded as the second-largest market worldwide, with digital advertising accounting for more than 50 % of a film's total expenditure, exploring the marketing effects of social platforms on box office performance in China is crucial for Hollywood studios. In this study, we defined a sequential process consisting of two marketing modes: broadcast before theatrical release and electronic word of mouth (eWOM) after release. The broadcast and eWOM modes were proxied by the volume and valence attributes of Maoyan and Douban, the two popular and professional platforms for video entertainment.

Volume and valence on Maoyan and Douban were found to influence gross revenue, but volume on Maoyan has the highest predictive power. Marketing on Maoyan is primarily broadcast marketing, whereas that on Douban is only eWOM marketing. Additionally, Hollywood hits depend on sequential marketing to succeed. Distributors should allocate resources to increase the volume on Maoyan before a movie is released and volume and valence on Douban after its release.

1. A digital era of movie marketing

The majority of Hollywood movies scheduled for release in 2020 were delayed because of the COVID-19 pandemic, but *Ba Bai (The Eight Hundred)* was released that year and ranked as the highest-grossing movie worldwide in terms of box office revenue. In 2021, China reported the highest box office revenue worldwide—approximately US \$7.3 billion ()—and indicated that its share in the global box office had increased to 25.4 %, surpassing that of the United States, which was previously considered the largest market worldwide (Thomala, 2022). The economic development pattern of China has fostered a middle class with high income, and demand for entertainment has thus considerably increased. After the pandemic, China is expected to gain an even greater share of the global box office (Thomala, 2022). Because of fierce competition from streaming services, Hollywood studios tend to rely on international markets, particularly China, to recoup their costs and maximize box office revenue.

Many challenges are encountered during the distribution of non-Chinese movies to the Chinese market because China has specific quotas for foreign movies and Chinese moviegoers have a distinct taste.

Hollywood hits usually have global marketing expenditures exceeding US\$150 million, which represents at least 50 % of a movie's total budget (Guttmann, 2022; Rainey, 2016; Sweeney, 2018). Therefore, Hollywood studios must identify the marketing modes that create blockbusters in China and understand their effects on box office success.

This study aims to uncover the marketing modes that create blockbusters in China and to determine their effects on box office success. Marketing strategies for Hollywood studios can be derived accordingly. In China, social platforms are embedded within a walled garden ecosystem and are a tool for mass media and interpersonal communication. Therefore, we defined a sequential marketing process in that the broadcast mode occurs before and during the release of a movie, whereas the eWOM mode occurs after release (Baek, 2017, p. 20). To the best of our knowledge, this is the first study to define broadcast and eWOM marketing as a sequential process for the Chinese market.

We continued to establish proxies for measuring the effects of broadcast and eWOM marketing. Our literature review revealed that volume and valence are the most cited proxies for social media engagements. Most studies on Chinese movie marketing have analyzed Weibo posts. In this study, we instead focused on Maoyan and Douban

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because they are two popular and professional platforms for video entertainment. The research questions were stated as follows: *Do volume and valence on Maoyan and Douban influence a movie's gross box office revenue? Furthermore, do volume and valence on Maoyan and Douban exhibit the broadcast or eWOM mode of marketing?*

We collected data on Maoyan and Douban and clustered 957 movies released from 2012 to 2019, before the pandemic, into two groups on the basis of their budget: 248 high-budget movies including Hollywood and Chinese hits and 709 low-budget movies. Random forest (RF) tests demonstrated the strong predictive power of Maoyan and Douban for a movie's box office performance. In addition, the regression tests led us to validate sequential marketing when all other variables are controlled for. Maoyan primarily operates in broadcast mode, whereas Douban only provides eWOM. No significant differences were found between the marketing modes of high- and low-budget movies. Compared with Hollywood hits, low-budget movies nevertheless rely more on digital marketing to succeed.

The remainder of this paper is organized as follows. Section 2 describes the history of Chinese cinema in detail and provides an introduction to Douban and Maoyan. Section 3 discusses the theories underlying broadcast and eWOM marketing and establishes a model of sequential marketing. Section 4 presents data sources and our algorithmic models, the RF model and polynomial regression tests. Section 5 presents the empirical results and a discussion. Section 6 provides an integrated analysis of our empirical results and marketing strategies. Finally, Section 7 concludes the paper.

2. Chinese movie market and marketing

2.1. Hollywood on the Chinese market

In 2001, China reformed its movie distribution system to establish private and interprovince cinema chains and enable the import of Hollywood and Hong Kong movies within a quota control mechanism (CineHello, 2017). In 2010, the Chinese government issued a series of movie policies to boost the industry. Between 2012 and 2015, box office revenue increased substantially, with Chinese movies accounting for more than 50 % of total revenue (QianZhan, 2021) This growth of box office revenue in China was primarily due to increases in the number of screens and the moviegoing population in third- and fourth-tier cities (Table 1).

In 1994, China stated that 10 Hollywood movies could be released each year. This quota was expanded in 2001 to 20 movies in response to China's negotiation for membership of the World Trade Organization (WTO). In 2012, China signed the Memorandum of Understanding and

Table 1
Box office revenue in China from 2013 to 2023.

Year	Number of screens	Box office rev. (CN¥ billion)	Top grossing movie	Box office rev. of top grossing movie (CN¥ billion)
2013	18,195	21.77	<i>Journey to the West</i>	1.25
2014	23,600	29.64	<i>Transformers: Age of Extinction</i>	1.98
2015	31,600	44.07	<i>Monster Hunt</i>	2.44
2016	41,129	45.71	<i>The Mermaid</i>	3.39
2017	50,776	55.91	<i>Wolf Warrior 2</i>	5.68
2018	60,079	60.98	<i>Operation Red Sea</i>	3.65
2019	69,787	64.26	<i>Ne Zha</i>	5.04
2020	75,581	20.42	<i>The Eight Hundred</i>	3.11
2021	82,248	47.26	<i>The Battle at Lake Changjin</i>	5.76
2022	83,998	30.07	<i>The Battle at Lake Changjin, II</i>	4.07
2023	86,310	54.92	<i>Full River Red</i>	4.54

Source: HuaJing Info (www.huaon.com), China Film Administration (www.chinafilm.gov.cn).

Resolving Film-Related Issues with the United States, permitting an additional 14 3D or IMAX movies per year amid the WTO bilateral negotiations.¹ Since then, the share of foreign movies released in China has increased from 13 % to 25 %, and these movies account for 40 % to 48 % of total box office revenue (Table 2).

During the outbreak of COVID-19, the number of foreign films released in China considerably decreased, and their market share of total gross revenue decreased to less than 15 % (Table 2). Consequently, the Chinese movie market gradually started to adapt to local tastes, and this change affected the ability of Hollywood studios to create movies that would be blockbusters in China. With the market share of North America decreasing to its pre-2011 level, Hollywood studios attempted to create new titles to expand their share of the Chinese market.

2.2. Movie marketing in China

In addition to the cast, director, and genre, the marketing and advertising of a movie are crucial to its success (Bogaert, Ballings, den Poel, and Oztekin, 2021). Social media platforms are considered optimal for movie marketing because of the low cost and rapid dissemination capability (Chen et al., 2020; Follows, 2016; Nan, 2022, p. 50; Yang, 2021). In China, major tech companies create walled garden ecosystems for their platform services, into which many affiliated or self-owned miniprograms—including instant messaging, information or video sharing, navigation, ride hailing, food delivery, e-commerce, payment, and investment—are incorporated. These closed ecosystems enable firms to retain their customers by increasing the costs of multihoming² (Chou and Wang, 2024). All platforms in China tend to offer mass media and peer-to-peer interaction features.

Three types of platforms are often used in cinema advertising and promotion. These platforms are news portals such as Sina, NetEase, and Sohu; professional movie websites such as Maoyan, Douban, and Mtime; and video streaming websites such as Youku, Tencent Video, and iQIYI (Nan, 2022, p. 50). Weibo, TikTok, Bilibili, and Xiaohongshu (Little Red

Table 2
Domestic and foreign movies released in China from 2013 to 2023.

Year	# of Domestic movies	Box office rev., domestic movies (CN billion)	Avg. box office sales, domestic movies (CN¥ million)	# of foreign movies	Box office rev., foreign movies (CN billion)	Avg. box office rev., foreign movies (CN¥ million)
2013	326	12.77	39.17	n.a.	9.00	n.a.
2014	308	16.16	52.47	80	13.48	168.50
2015	320	27.14	84.81	63	16.93	268.73
2016	297	26.66	89.76	90	19.05	211.67
2017	376	30.14	80.16	98	25.77	262.96
2018	383	37.90	98.96	122	23.08	189.18
2019	429	41.19	96.01	123	23.07	187.56
2020	208	17.09	82.16	86	3.33	38.72
2021	529	39.93	75.48	43	7.33	170.47
2022	272	25.51	93.79	54	4.56	84.44
2023	971	46.01	47.38	n.a.	8.91	n.a.

n.a.: not applicable.

Source: China Film Administration (www.chinafilm.gov.cn), NetEase (www.163.com), and HuaJing Info (www.huaon.com).

¹ This quota for major Hollywood studios was expanded to 34 movies per year (MaShangXiao, 2017). Notably, movies coproduced with China, such as *The Great Wall* (directed by Zhang Yimou), and presale movies imported by Chinese distributors were excluded from this quota.

² Multihoming indicates that users regularly share their life with friends on multiple social media platforms such as Facebook, Tiktok or Instagram, unlike their searching for information only with Google (single-homing).

Book) are also used to post and share movie-related information and comments (Yu, 2024, p. 80). Movie distributors post movie-related information and trailers on these platforms before a movie is released, and they post short videos on the cast, movie synopsis, off-screen clips, or ticket-sale records once the movie has been released (Mirror Entertainment, 2021).

Cross-platform marketing typically relies on a “one content for multiple platforms” format, in which short videos are initially posted on TikTok and various versions are later posted on other platforms. For example, the trailer for *My People, My Homeland* was re-edited into seven short videos with hashtags, and these videos reached 200 million views and attracted 1.5 million likes (Mirror Entertainment, 2021). Distributors often sign contracts with key opinion leaders for them to promote their movies, and viewers are directed to Maoyan, a platform that offers ticket-sale services (MouYu, 2024). Independent or arthouse movie producers often cooperate with e-commerce websites such as Taobao, Tmall, Jingdong, and Meituan to increase ticket sales because of the low costs of this type of promotion (Nan, 2022, p. 50).

2.3. Maoyan and Douban

Most studies on Chinese movie marketing have tended to analyze Weibo blogs (Liu, Ding, Chen, Chen, and Guo, 2014; Qiu et al., 2018; Tang, Winoto, Guan, and Chen, 2018). In this study, we reinforced the results of previous studies by focusing on two popular movie-specific platforms, namely Maoyan and Douban. Typically, distributors list information on their movie on Maoyan for ticket sales and on Douban for professional critique.

In 2012, Maoyan was launched as a movie ticket-sale platform for Meituan. After fierce competition between several online ticket-sale platforms, two platforms, namely Maoyan and Taobao Dianyian (a subdivision of Alibaba Group), emerged as a duopoly. In the second quarter of 2018, Maoyan and Taobao had a market share of 61.3 % and 37 %, respectively (Maoyan, 2022). Maoyan later became the leading movie portal, offering real-time box office data from theaters nationwide (Chen et al., 2020). In 2018, Maoyan reported 1.1 billion monthly page views, 150 million user ratings, and more than 150 million unique monthly visitors (Maoyan, 2019).

Douban is regarded as the Chinese version of IMDb. It displays users' reviews and ratings of movies released in China. Created in March 2005, Douban offers information on movies, books, and music and offers social interaction through user ratings and comments. In 2012, Douban expanded its business to movie ticket sales and now covers 81 movie theater chains in 33 major cities (Baidu Encyclopedia, 2012).

Douban attracted its first 1 million users within nearly 2 years, and the number of unique visitors reached 8.23 million by 2009 (Sun, 2013). Since 2012, its growth has been moderate compared to other Chinese social platforms because of the elite nature of its users (NetEase, 2012). In 2020, the number of registered accounts on Douban reached 75 million, and the platform had approximately 210 million daily page views (Quandata, 2024).

Unlike Maoyan's users, who are ordinary moviegoers, 70 % of Douban's users are between 18 and 34 years of age and live in first- and second-tier cities (Douban, 2023, pp. 1–2). Because 60 % of Douban's users have a college degree, they have a predisposition enjoying art and entertainment, with a preference toward drama, independent films, and documentaries (Maobo, 2017).

In terms of user interaction, users can post, share, comment on, and like movie reviews on both Maoyan and Douban. Maoyan's users predominantly post short comments, whereas Douban's users, including movie critics and professionals, prefer article-length critiques (Maobo, 2017). On Douban, all users can rate movies with a five-star system, whereas on Maoyan, only users who have purchased a ticket can rate a movie with the same rating system (Maobo, 2017).

2.4. High- and low-budget movies

Although Chinese cinema dominates the Chinese film market and box office revenue, the average gross revenue of foreign movies is generally higher (Table 2). This discrepancy underscores the difference between local and foreign movies in the Chinese market. As mentioned previously, marketing costs and filming budgets are positively correlated (Guttman, 2022). Therefore, we assumed that the marketing modes of Hollywood hits differ from those of small-budget movies, such as independent and arthouse movies. Our first hypothesis was as follows.

H1. High- and low-budget movies involve different marketing modes.

In this study, we conducted a cluster analysis to stratify movies on the basis of their budget. We used *K*-means clustering to minimize the least-squares distance from the center of each cluster *K*,³ and we obtained *K* = 2 through iterative tests. Movies were divided into high and low-budget movies. Fig. 1 presents the distinctive distribution of the valence scores for the two types of movies.

The high-budget movies included 248 Hollywood and Chinese hits with an average gross revenue of CN¥197.13 million and an average budget of US\$58.2 million (Table 3). The low-budget movies included 709 Chinese movies with an average gross revenue of CN¥96.92 million and an average budget of US\$1.7 million. On both Douban and Maoyan, the high-budget movies were associated with higher volume and valence scores compared to low-budget movies (Table 3). On Douban, the number of users who rated movies was higher than the number of users who reviewed movies, indicating that users review movies less frequently than they rate them because reviewing is time-consuming and effortful.

3. Broadcast and eWOM marketing

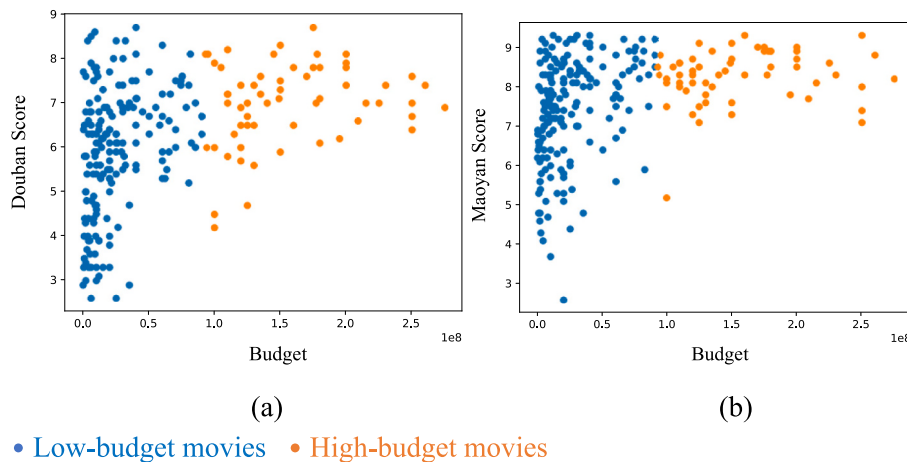
3.1. Sequential marketing process

Baek (2017, p. 20) differentiated between broadcast and eWOM marketing by their timeline. The author argued that the broadcast mode is more influential during the initial stage of a movie's release, whereas eWOM is more influential during the late stage. Gong, Zhang, Zhao, and Jiang (2017) reported that eWOM was more effective than broadcast mode in explaining movie performance. However, Chen et al. (2020) indicated that, compared to eWOM, the broadcast mode had a stronger effect on ticket sales.

Multiple studies also have indicated that eWOM has a lagged effect on box office revenue because the diffusion of information takes time (Godes & Mayzlin, 2009, p. 731; Karniouchina, 2011, p. 67). For instance, Castillo et al. (2021, p. 9) argued that release-day performance is affected by blog volume and advertising before the day of release, whereas postrelease performance is affected by postrelease blog valence and advertising. Ding et al. (2017, p. 81) provided empirical evidence indicating that an increase in the number of likes on a movie's IMDb page in the week before its release strongly affects its opening-week ticket sales but that this effect weakens over time. Taken together, these findings indicate that eWOM and broadcast modes affect box office revenue at different stages during the release cycle of a movie.

We consequently considered a sequential process involving two marketing modes: broadcast before theatrical release and eWOM after release. As illustrated in Fig. 2, the broadcast mode occurs before a movie's release through official or key opinion leader accounts, whereas eWOM occurs after the opening day through users' posts to their friends,

³ *K*-means clustering is an algorithm used to divide *n* observations into *k* ($\leq n$) sets. This algorithm minimizes the within-cluster sum of squares for a given set S_i to determine *k* as follows: $\arg\min_s \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2 = \arg\min_s \sum_{i=1}^k |S_i| \text{Var} S_i$, where μ_i is the mean of the points in S_i (FF1).



Douban score: A movie’s rating score in Douban

Maoyan score: A movie’s rating score in Maoyan

Fig. 1. Cluster analysis of films released in China from 2012 to 2019.

Table 3
Comparison of high- and low-budget movies.

Variable	Total	High budget	Low budget
Numbers	957	248	709
Average gross revenue (CN¥ million)	122.88	197.13	96.92
Average percentage of gross revenue accounted for by opening-weekend revenue %	51.47	47.37 %	52.90 %
Average budget (US\$ million)	15.1	58.2	1.7
Average number of Maoyan users rating a movie (<i>Maoyan_vote</i>)	83,591	115,676	72,366
Average rating score in Maoyan (<i>Maoyan_score</i>)	6.825	7.651	6.536
Average number of Douban users rating a movie (<i>Douban_vote</i>)	52,071	97,134	36,309
Average rating score in Douban (<i>Douban_score</i>)	4.924	6.099	4.513
Average number of Douban users reviewing a movie (<i>Douban_user</i>)	23,110	38,495	17,729
Average p/n value ^a of the reviews in Douban (<i>Douban_value</i>)	2.76	5.36	1.85

Source: author.

^a Ratio of positive to negative reviews per movie on Douban.

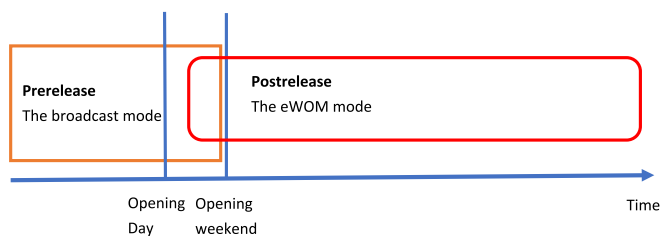


Fig. 2. Sequential process of digital marketing.

family, and wider network (Baek et al., 2017, p. 18; Ding, Cheng, Duan, and Jin, 2017). Typically, eWOM becomes ubiquitous when a large number of viewers share posts.

Opening-weekend (i.e., Friday through Sunday) box office revenue accounts for approximately one-third of all a movie’s gross box office revenue (Turner, 2015) and thus can be a robust indicator of a movie’s financial success (Oh et al., 2017, p. 32). In this study, we presumed that opening-weekend box office revenue is affected by broadcast marketing. We also hypothesized that eWOM marketing influences box office

revenue after the opening weekend because of its lagged effect (Baek et al., 2017, p. 18; Ding, Cheng, Duan, and Jin, 2017).

A percentage term, namely the contribution of opening-weekend box office revenue to gross box office revenue, was used to measure the effects of broadcast and eWOM marketing. Stronger broadcast marketing is postulated to generate higher opening-weekend box office performance, leading to a larger contribution to gross revenue. By contrast, weaker broadcast marketing results in lower opening-weekend box office performance, leading to a smaller contribution to gross revenue. Strong eWOM, conversely, increases box office revenue after the opening weekend, leading to a small contribution of opening-weekend revenue to gross revenue. The weak eWOM does not increase box office revenue after the opening weekend, leading to a large contribution to gross revenue.

3.2. Volume and valence

Our literature review revealed that volume and valence are the most cited proxies for social media engagements (Asur and Huberman, 2010; Chen et al., 2020; Dellarocas et al., 2007, pp. 23–25; Rui et al., 2013, p. 867). Volume refers to the number of individuals to whom eWOM is transmitted, or the quantity of information provided by the sender or received by followers, whereas valence refers to a statement that endorses or suggests the boycotting of a product or service (Buttle, 1998).

Several studies have compared the effect of volume with that of valence in determining movie sales and demonstrated the effectiveness of volume (Duan, Gu, and Whinston, 2008; Lipizzi, Iandoli, and Marquez, 2016; Liu, 2006). Some others have underscored the influence of valence in predicting box office success (Chintagunta, Gopinath, and Venkataraman, 2010; Bhattacharjee, Sridhar, and Dutta, 2017, p. 365; Eliashberg and Shugan, 1997). The rest of the works reported that both volume and valence have significant influences on gross revenue (Apala et al., 2013; Asur and Huberman, 2010; Basuroy, Chatterjee, and Ravid, 2003).

Eliashberg and Shugan (1997) reported that the number of reviews made by critics statistically predicted the gross revenue of a movie only during the opening week. Deng (2020, p. 1246) compared users’ reviews of movies with those of critics and reported that users’ reviews were an average of moviegoers’ opinions, more plausible than “respective eulogy”. Taken together, these findings indicate that structured numeric valence in users’ reviews has a stronger association with ticket sales than does that of critics’ unstructured textual narratives.

Basuroy, Chatterjee, and Ravid (2003) determined that the effect

originating from negative valence was stronger than that originating from positive valence. Chen et al. (2020, pp. 1567–1568) discovered that negative reviews had a stronger effect on box office revenue compared to positive reviews. Park et al. (2017, pp. 155 & 156) reported that, in the context of credibility, production studio biases were often reflected by positive reviews. They corroborated that negative tweets had stronger effects on gross revenue than did positive tweets. They also revealed that the influence of negative tweets exhibited an increasing return on gross revenue (i.e., the convex impact), whereas that of positive tweets exhibited a decreasing return (i.e., the concave impact) (Park et al., 2017, pp. 149–156). Kim, Hong, and Kang (2015) also estimated the nonlinear relationships between online reviews and box office performance.

As stated previously, strong broadcast marketing induces a larger contribution of opening-weekend ticket sale to gross revenue while strong eWOM marketing entails a small contribution of opening-weekend revenue. We then used volume and valence on the Maoyan and Douban platforms as proxies for the effects of broadcast or eWOM marketing. Our second hypothesis was as follows.

H2a. On Maoyan and Douban, volume and valence increase the gross box office revenue of movies.

H2b. On Maoyan and Douban, volume and valence increase the contribution of opening-weekend box office revenue to gross revenue should strong broadcast marketing be present.

H2c. On Maoyan and Douban, volume and valence decrease the contribution of opening-weekend box office revenue to gross revenue should strong eWOM marketing be present.

We defined volume as the number of users on Maoyan or Douban who rated a movie or the number of users who posted comments about the movie. In terms of valence, numeric ratings are considered to be more plausible than are textual comments (Deng, 2020, p. 1246).

Maoyan and Douban convert users’ movie ratings from a five-star system into a 10-point Likert-type scale. Hence, valence was considered as the average rating for a movie on Maoyan or Douban. Douban also provides the ratios of positive, negative, and neutral comments for each movie. In this study, we extracted the ratio of positive to negative comments (p/n value) and employed it as another valence variable (Table 4).

3.3. Measurement methods

Four models are often used to examine the effects of social platform marketing on box office performance: linear regression, polynomial regression, support vector machine, and RF (Chen et al., 2020; Huang & Pai, 2020, pp. 8 & 9; Oh, Roumani, Nwankpa, and Hu, 2017). For example, Ahmad, Bakar, and Yaakub (2020) employed four machine learning algorithms—linear regression, support vector machine, the multilayer perceptron neural network, and RF—to predict movie revenue on sentiment in comments on YouTube trailers.

To understand the predictive power of volume and valence features in determining gross box office performance, RF tests were performed in this study. Because RF consists of multiple decision trees to produce the final output, it tends to be more accurate and robust than individual trees (Breiman, 2001). It is particularly useful in determining the contribution of features to the prediction, that is, which features are most influential in predicting the target outcome.

However, RF is weak for explaining the detailed relationships between variables. We decided to complement RF with regression tests (Rawlings, Pantula, and Dickey, 1998). The tests could articulately specify the relationships between volume/valence attributes and the contribution of opening-weekend ticket sales and, therefore, differentiate broadcast and eWOM marketing. As mentioned previously, the valence variables may exhibit nonlinearity against gross revenue (Kim, Hong, and Kang, 2015; Park et al., 2017, pp. 149–156). We instead

Table 4 Variables.

Variable	Description	Mean μ (Standard Deviation)	Source
Dep. Var.:			
<i>Box_office</i>	A movie’s box office revenue in the 2 months after its release (CNY million)	122.88 (343.01)	Maoyan
<i>Box_office_p</i>	Percentage of gross revenue accounted for by opening-weekend revenue (=Box_office)	0.515 (0.201)	Generated
Indep. Var.: Volume			
<i>Maoyan_vote</i>	Number of users who rated a given movie on Maoyan	83,591 (267,896)	Maoyan
<i>Douban_vote</i>	Number of users who rated a given movie on Douban	52,071 (105,164)	Douban
<i>Douban_user</i>	Number of users who shared comments on a given movie over Douban	23,110 (48,772)	Douban
Indep. Var.: Valence			
<i>Maoyan_score</i>	Average rating score for a given movie on Maoyan	6.825 (1.969)	Maoyan
<i>Douban_score</i>	Average rating score for a given movie on Douban	4.924 (1.968)	Douban
<i>Douban_value</i>	p/n value = ratio of positive to negative comments on Douban	2.760 (5.799)	Douban
Control Var.:			
<i>Budget</i>	A movie’s production cost (US\$ million)	15.1 (46.1)	IMDb
<i>Nation</i>	1 = Hollywood, 2 = other regions, 0 = domestic (China)	0.192 (0.483)	Maoyan/ generated
<i>Season</i>	1 = holiday season (Lunar New Year, May 1st holiday, summer, October 1st holiday) 0 = nonholiday	0.125 (0.331)	Maoyan, State Council of China
<i>Screen_no</i>	The number of screens showing a given movie	20,173 (920.519)	Maoyan
<i>Sequel</i>	1 = sequel, 0 = nonsequel	0.079 (0.271)	Maoyan/ generated
Control Var.: Genre			
Drama	1 = drama, 0 = not drama	0.363 (0.481)	Douban
Romance	1 = romance, 0 = not romance	0.283 (0.451)	Douban
Sci-fi	1 = sci-fi, 0 = not sci-fi	0.057 (0.233)	Douban
Kung-fu	1 = kung-fu, 0 = not kung-fu	0.013 (0.116)	Douban
History	1 = ancient dynasty, 0 = not ancient dynasty	0.024 (0.153)	Douban
Horror	1 = horror, 0 = not horror	0.060 (0.237)	Douban
Adventure	1 = adventure, 0 = not adventure	0.176 (0.381)	Douban
Comedy	1 = comedy, 0 = not comedy	0.329 (0.470)	Douban
Cartoon	1 = cartoon, 0 = not cartoon	0.160 (0.367)	Douban
Children’s/ family	1 = children’s, 0 = not children’s	0.027 (0.163)	Douban

Source: author.

adopted polynomial regression that models the non-linear patterns more effectively than the linear counterpart.

4. Modeling the effects of sequential marketing

4.1. Data collection

Because Maoyan has offered ticket services since 2012, we collected data on Douban and Maoyan for the period 2012 to 2019, before the pandemic disrupted theatrical release. Our database consisted of 957 movies in Douban and Maoyan, with budget information obtained from IMDb (Table 4).

In the studies of predicting Hollywood box office performance, factors such as movie budget, number of theaters screening the movie, genre, release date, sequel status, country, director, studio, distributor,

Motion Picture Association rating, and nomination for best picture are often included in the models (Abidi, Xu, Ni, Wang, and Zhang, 2020; Baek et al., 2017, p. 19; Castillo, Benitez, Llorens, and Luo, 2021; Kang, 2021; Ruus and Sharma, 2020, p. 989). Deng (2020, p. 1248) explored the effects of online reviews on box office performance while controlling for the effects of screen number, marketing cost, budget, release date, and genre. In this study, we used genre, country of origin, screen number, release date, sequel status, and budget as control variables in our models (Table 4). To control disturbances originating from price inflation in longitudinal data, we set the 2012 consumer price index to 100 % to deflate the variables *Box_office* and *Budget*.

Table 4 shows that the mean for *Box_office_p* is 0.515, that is, the opening weekend ticket sale contributes half of gross revenue. The average number of screens showing a given movie (*screen_no*) is 20,173. About 12.5 % of movies are screened during the holiday season (*season*), and only 8 % of movies have sequels. The most proliferated genre screened in China between 2012 and 2019 is drama (36.3 %), followed by comedy (32.9 %).

Table 5 shows the correlation matrix for the selected variables. Significant positive correlations were found between all volume and valence attributes, and gross box office revenue. Meanwhile, significant negative correlations were found between the attributes, except for valence on Maoyan, and the percentage of gross revenue accounted for by opening-weekend box office sale, suggesting that they might increase box office revenue via eWOM marketing.

4.2. RF model

We first used RF to determine the feature importance for the box office revenue in China. Fig. 3 illustrates that the RF method combines all generated decision trees through a bagging (or bootstrap aggregation) algorithm. Each bootstrap subset is obtained by randomly selecting n observations from S_n with replacement, where the probability of each observation being selected is $1/n$. Let $X = x_1, x_2, \dots, x_m$ represent the input vector containing m features, and let Y represent the value of gross revenue. The training set S_n containing n observations can be expressed as follows:

$$S_n = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)\}, X \in R^m, Y \in R. \quad (1)$$

In this study, we used an n -fold method to divide data into training and test samples before bootstrapping and ensure the robustness of our experimental results.

RF regression involves using the K tree-structured base classifier $h(X, \Theta_k)$, where $K = \{1, \dots, k\}$ and Θ_k represents the parameter and structure of the k th decision tree. Once the bagging algorithm has identified a set of bootstrap samples $(S_n^{o_1}, \dots, S_n^{o_k})$, a tree decision algorithm is applied to these samples to obtain a collection of k prediction trees $\hat{h}(X, S_n^{o_1}), \dots, \hat{h}(X, S_n^{o_k})$. Finally, aggregation is performed by averaging the outputs of all trees. Thus, \hat{Y} is obtained as follows:

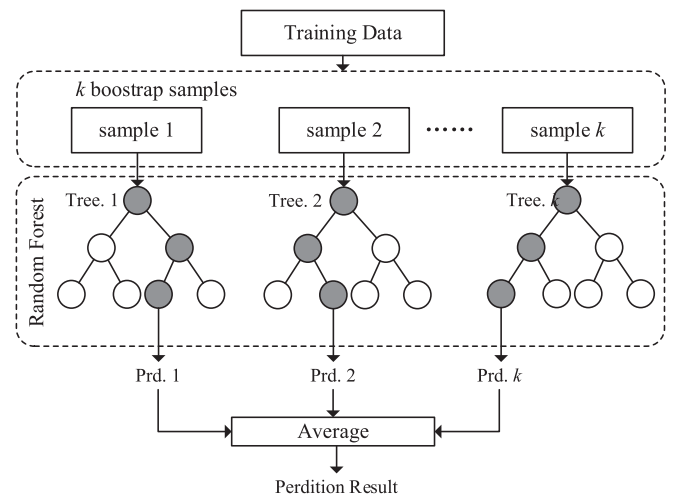


Fig. 3. RF model training.

$$\hat{Y} = \frac{1}{k} \sum_{l=1}^k \hat{Y}_l = \frac{1}{k} \sum_{l=1}^k \hat{h}(S_n^{o_l}) \quad (2)$$

where \hat{Y}_l is the output of the l th tree.

The scores associated with the features were normalized using the differences in standard deviations before and after tree permutation when measuring the importance of the features. For the score, features producing large values are regarded more important than those producing small values.

4.3. Polynomial regression

We also performed polynomial regression tests to examine the relationships between volume and valence attributes and the dependent variable—the percentage of gross revenue accounted for by opening-weekend revenue—while controlling for the nonlinearity of valence (Fan, 1996, pp. 1–5). The following equation is a polynomial regression equation used to estimate Y_i (*Box_office_p*):

$$Y_i = \alpha + \beta X_i + \gamma Vol_i + \delta Val_i + \rho Val_i^2 + \theta G_i + \epsilon_i \quad (3)$$

where $E(\epsilon_i) = \mu$; $Var(\epsilon_i) = \sigma^2$; X_i represents movie-related information, such as screen number, budget, sequel status, nationality, and release date; Vol_i represents volume attributes; Val_i represents valence attributes; Val_i^2 is the quadratic term for valence attributes; G_i denotes a set of discrete genres including drama, romance, horror, sci-fi, kung-fu, history, horror, adventure, comedy, cartoon, and family; and $\beta, \gamma, \delta, \rho, \theta$ is the coefficient estimates.

For the coefficient estimate ρ , a positive value suggests a convex

Table 5

The correlation matrix of the selected variables.

	<i>Box_office</i>	<i>Box_office_p</i>	<i>Maoyan_vote</i>	<i>Douban_vote</i>	<i>Douban_user</i>	<i>Maoyan_score</i>	<i>Douban_score</i>	<i>Douban_value</i>	<i>Budget</i>	<i>Screen_no</i>
<i>Box_office</i>	1.000									
<i>Box_office_p</i>	-0.260*	1.000								
<i>Maoyan_vote</i>	0.930*	-0.170*	1.000							
<i>Douban_vote</i>	0.631*	-0.327*	0.561*	1.000						
<i>Douban_user</i>	0.770*	-0.298*	0.732*	0.859*	1.000					
<i>Maoyan_score</i>	0.273*	0.065*	0.259*	0.473*	0.330*	1.000				
<i>Douban_score</i>	0.170*	-0.153*	0.125*	0.322*	0.334*	0.491*	1.000			
<i>Douban_value</i>	0.225*	-0.207*	0.186*	0.493*	0.473*	0.346*	0.542*	1.000		
<i>Budget</i>	0.228*	-0.160*	0.115	0.318*	0.234*	0.247*	0.335*	0.288*	1.000	
<i>Screen_no</i>	0.917*	-0.237*	0.886*	0.644*	0.811*	0.344*	0.191*	0.268*	0.237*	1.000

*Refers to the 5 % significance level.

Source: author.

relationship (that is, an increasing return on *Box_office_p*), and a negative value suggests a concave relationship (that is, a decreasing return on *Box_office_p*) (Park et al., 2017, p. 152).

A least-squares algorithm is often used to estimate coefficients in a linear form to ensure efficiency, even when nonlinearity is assumed (Freeman, 2009, p. 26). Because a movie's release cycle acts like an independent event, our database is viewed as cross-sectional. Ordinary least square (OLS) regression is perfectly applicable to the estimation on cross-sectional data (Elberse and Eliashberg, 2003; Oh et al., 2017, p. 700). It is noticeable that, although imperfect collinearity is found between volume and valence attributes (Table 5), the overall fit of regression is not affected (Kennedy, 2008, pp. 196–197).

5. Results: Impacts of broadcast and eWOM marketing

5.1. Feature importance of volume on Maoyan

Because significant correlations were confirmed between volume (*Maoyan_vote* and *Douban_vote*), valence (*Maoyan_vote* and *Douban_vote*), budget, the screen number, sequel, release date (*season*), three genres and gross revenue (*Box_office*), we included these features in the RF tests. The results are illustrated in Fig. 4.

The screen number variable was found to generate an estimated value of 0.485, volume on Maoyan generated an estimated value of 0.441, volume on Douban generated an estimated value of 0.037, valence on Maoyan generated an estimated value of 0.014, valence on Douban generated an estimated value of 0.011, budget generated an estimated value of 0.005, release date and sequel each generated an estimated value of 0.002, and three genres each generated an estimated value of 0.001–0.002. The number of screens showing a given movie and volume on Maoyan thus generated the top two estimated values, together with a weight of 93.6 % in predicting box office performance. These results indicated that volume on Maoyan had the highest predictive power of all volume and valence features.

Volume features were found to be more important ($0.478 = 0.441 + 0.037$) than valence features ($0.025 = 0.014 + 0.011$) in determining box office performance (Fig. 4). That is, the success of box office performance depends more on user diffusion than well-received comments. The estimated value for volume plus valence on Maoyan ($0.455 = 0.441 + 0.014$) was higher than that for Douban ($0.048 = 0.037 + 0.011$), indicating that Maoyan is more able to predict the gross revenue of movies.

Fig. 5 compares the RF results for high- and low-budget movies. Of all the features, the screen number and volume on Maoyan were discovered to have the highest predictive power for high-budget and low-budget movies, respectively (Fig. 5a, b). The results indicate that social media platforms, proxied by volume and valence, have a stronger predictive effect on the ticket sales of low-budget movies ($0.727 = 0.693 + 0.013 + 0.017 + 0.004$) than on those of high-budget movies ($0.438 = 0.361 + 0.018 + 0.044 + 0.015$). Therefore, low-budget movies considerably rely on social media diffusion (user volume) to succeed.

5.2. Maoyan as the broadcast mode

In Table 6, columns A and B present the results for volume and valence attributes against the opening-weekend revenue of high-budget movies in relation to gross revenue (*Box_office_p*). The estimated coefficient for volume on Maoyan was approximately 0.08, indicating that a 1 % increase in volume on Maoyan corresponded to a 0.08 % increase in the contribution of the opening-weekend box office to gross revenue. However, the estimation of valence on Maoyan was insignificant. As stated in H2b, Maoyan was confirmed to involve the broadcast mode for high-budget movies that occurs before film release and increases the contribution of opening weekend ticket sales to its gross revenue. Specifically, the volume on Maoyan comprises the broadcast mode.

In Table 6, columns C and D present OLS results for low-budget movies. The coefficient estimates for volume on Maoyan were approximately 0.05–0.06. Each 1 % increase in volume on Maoyan corresponded to a 0.05 % to 0.06 % increase in the contribution of a low-budget movie's opening-weekend revenue to its gross revenue. These results reveal that volume on Maoyan primarily consists of broadcast marketing for low-budget movies.

For valence on Maoyan, its linear coefficient was approximately estimated at 0.09, and the estimated coefficient for the quadratic term was -0.008 . The negative direction indicated in the quadratic term's coefficient further corroborates the concavity of valence on Maoyan, indicating that the magnitude of eWOM effect diminishes over time. In Fig. 6, Maoyan rating was predicted to initially increase the percentage of opening weekend revenue and decrease the percentage when it exceeded 6 points. Each 1-point increase corresponded to the contribution of opening-weekend revenue to gross revenue decreasing by 0.01 % [$-0.012 = 0.09 + 2 \times (-0.008) \times 6.536$].⁴ The results indicate that Maoyan's valence yields minor eWOM effects for low-budget movies.

The significance levels were set at 5 %.

Because Maoyan is a ticket presale website on which distributors promote movies before their theatrical release, any increase in the number of Maoyan users who rated a movie upon its release is likely attributable to broadcast marketing. Valence on Maoyan, conversely, yields tiny, almost undistinguishable, eWOM effects for low-budget movies. Together, volume on Maoyan is regarded as a measure of a movie's popularity and an effective predictor of opening-weekend box office revenue.

5.3. Douban as the eWOM mode

5.3.1. Douban for high-budget movies

Douban_vote, the Douban volume attribute, had an estimated coefficient that was significant negative (-0.072) (Table 6, columns A). A 1 % increase in the number of Douban's users rating a high-budget movie was found to correspond to a 0.07 % decrease in the percentage of gross revenue, with the opening-weekend box office revenue accounted for.

For *Douban_score*, its linear and quadratic coefficients were significantly estimated as 0.083 and -0.008 (Table 6, columns A). For each 1-point increase in Douban rating, the contribution of opening-weekend revenue to gross revenue decreased by approximately 0.02 % [$-0.015 = 0.083 + 2 \times (-0.008) \times 6.099$]. The negative estimation on the quadratic term corroborated the concavity. The Douban rating initially raised the percentage of opening weekend revenue to gross revenue and decreased the percentage since reaching 5 points (Fig. 6). These results indicate that Douban has developed eWOM for high-budget movies. As a result of lagged diffusion, Douban's eWOM becomes apparent after the opening weekend.

Another set of Douban attributes (*Douban_user* and *Douban_value*), namely the number of commenting users and the p/n values associated with their comments, was found to fail to generate significant coefficient estimates. Textual comments were less effective than numeric ratings in predicting box office performance, consistent with Deng's findings (2020). Compared to comments with linguistic ambiguity, numeric values are easier to understand by viewers, thereby serving as useful information signals.

5.3.2. Douban for low-budget movies

Douban_vote and *Douban_user* were found to generate significant negative coefficient estimates of -0.045 and $-1.03e^{-6}$ (Table 6, columns C and D). As a result of the lagged effect of eWOM, any increase in

⁴ With reference to (F3), the total—linear plus quadratic—estimated impact for a 1-point increase in rating is expected to be $\delta + 2p \times \mu_{Val}$ where μ_{Val} is the mean for a given valence attribute (James, Witten, Hastie, and Tibshirani, 2021). The mean scores for valence variables are recorded in Table 3.

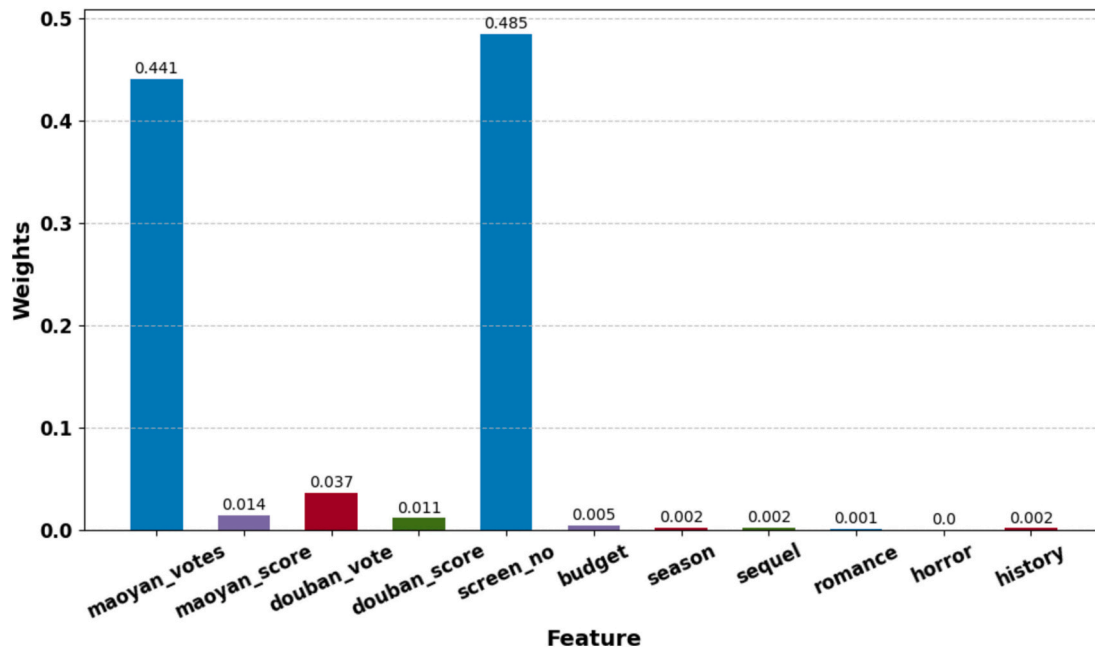


Fig. 4. Feature importance of volume and valence.

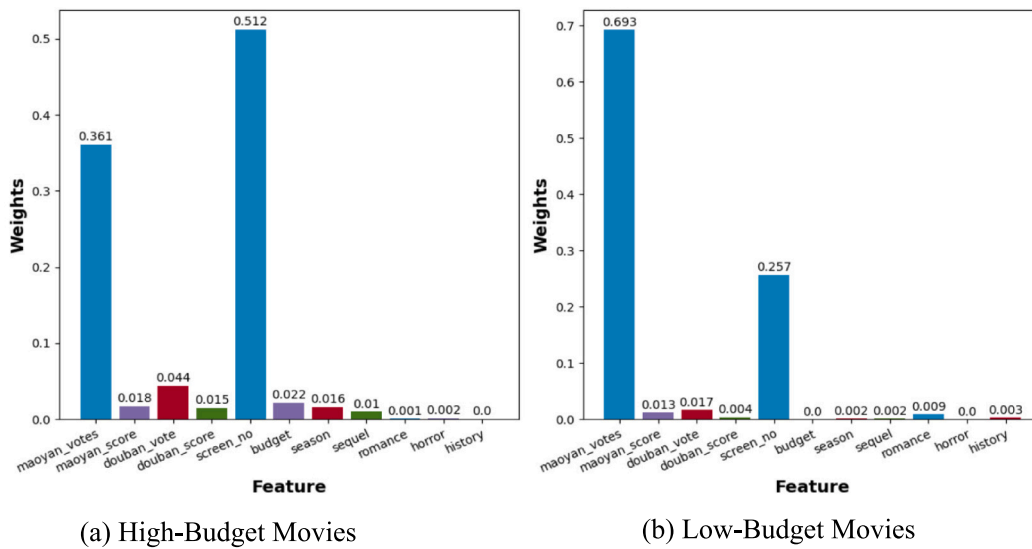


Fig. 5. Feature importance of volume and valence for high- and low-budget movies.

the number of Douban users rating or commenting on a movie led to an increase in the contribution of box office revenue after the opening weekend to gross revenue. Nevertheless, the impact made by commenting users was found to be considerably smaller than that made by rating users.

The estimated coefficients of *Douban_score* (0.07) and its quadratic term (-0.008) entailed a 0.002 % [$-0.002 = 0.07 + 2 \times (-0.008) \times 4.513$] decrease in the contribution of opening-weekend revenue to gross revenue. The eWOM effects originating from Douban ratings weakened throughout a theatrical movie release as a result of diminishing returns. Additionally, the estimated coefficient for *Douban_value* was -0.009 at the 5 % significance level. When the p/n value derived from Douban comments increased by 1 point, the contribution of revenue after the opening weekend to gross revenue was found to increase by 0.009 %. This eWOM effect did not change throughout a movie’s theatrical release because the associated quadratic term did not yield a

significant estimate.

5.4. Control and genre variables

In terms of control variables, the coefficient estimates of the number of screens for both low- and high-budget movies were significant at the 0.1 % level. The number of screens involves lagged effects, with the revenue of movies after the opening weekend increasing with the number of screens. The coefficient of country of origin (*nation*) for high-budget movies was 0.036–0.039, significant at the 5 % level. The contribution of opening-weekend revenue to gross revenue for Chinese high-budget movies exceeded that for Hollywood hits.

The coefficient estimate for the horror and thriller genre was negative and significant for both low- and high-budget movies. Because the success of many horror movies depends on special effects, their quality is difficult to evaluate on the basis of online information alone. Therefore,

Table 6
Marketing effects due to volume and valence attributes.^a

Variable	(A) % of gross revenue by opening-weekend revenue (high budget)	(B) % by of gross revenue by opening-weekend revenue (high budget)	(C) % by of gross revenue by opening-weekend revenue (low budget)	(D) % by of gross revenue by opening-weekend revenue (low budget)
Intercept	1.200*** (0.277)	1.256*** (0.294)	0.554*** (0.060)	0.631*** (0.055)
MAOYAN_vote#	0.083*** [0.011]	0.082*** [0.011]	0.056*** [0.007]	0.052*** [0.007]
MAOYAN_score	-0.017 [0.071]	-0.010 [0.074]	0.093*** [0.013]	0.091*** [0.012]
MAOYAN_score ²	-0.001 [0.005]	-0.002 [0.005]	-0.008*** [0.001]	-0.008*** [0.001]
DOUBAN_vote#	-0.072*** [0.020]		-0.045*** [0.012]	
DOUBAN_score	0.083** [0.032]		0.070*** [0.017]	
DOUBAN_score ²	-0.008** [0.003]		-0.008*** [0.002]	
DOUBAN_user#		-4.11e-07 [3.29e-07]		-1.03e-06*** [3.15e-07]
DOUBAN_value		-0.005 [0.004]		-0.009* [0.004]
DOUBAN_value ²		0.001 [0.001]		0.001 [0.001]
NATION	0.039* [0.017]	0.036* [0.017]	0.047* [0.023]	0.040 [0.023]
SEASON	-0.060 [0.031]	-0.055 [0.030]	-0.019 [0.023]	-0.001 [0.001]
SCREEN_NO#	-0.058*** [0.008]	-0.063*** [0.008]	-0.035*** [0.006]	-0.043*** [0.005]
SEQUEL	0.045 [0.033]	0.032 [0.035]	-0.029 [0.026]	-0.048 [0.026]
BUDGET#	-0.002 [0.007]	-0.008 [0.007]	Omitted	omitted
GENRE				
Drama	0.007 [0.022]	0.001 [0.023]	-0.018 [0.017]	-0.018 [0.017]
Romance	0.003 [0.027]	-0.008 [0.029]	0.006 [0.016]	0.010 [0.016]
Sci-Fi	0.015 [0.028]	-0.001 [0.028]	0.034 [0.056]	0.029 [0.056]
Kung-FU	-0.003 [0.088]	-0.033 [0.092]	-0.053 [0.067]	-0.053 [0.067]
History	-0.045 [0.062]	-0.055 [0.065]	-0.028 [0.054]	-0.052 [0.055]
Horror/thriller	-0.060* [0.027]	-0.063* [0.029]	-0.111*** [0.023]	-0.091*** [0.023]
Comedy	0.002 [0.025]	0.005 [0.026]	0.019 [0.015]	0.017 [0.015]
Children's	-0.052 [0.148]	-0.126 [0.154]	0.013 [0.037]	0.013 [0.038]
Cartoon	0.003 [0.036]	0.022 [0.038]	-0.003 [0.027]	0.031 [0.026]
Adventure	-0.020 [0.024]	-0.026 [0.025]	-0.023 [0.022]	-0.022 [0.023]
Sample size	248	248	709	709
Degree of freedom	F(21, 226)	F(21, 226)	F(20, 688)	F(20, 688)
F-value	8.82***	7.28***	17.64***	16.74***
Adjusted R-square value	0.400	0.348	0.320	0.308

x refers to the estimated values of coefficients β , γ , δ , ρ , and θ ; $[x]$ represents the standard error; $x\#$ represents variables algebraically transformed into logarithmic format; and x^2 represents the quadratic term. *5 % significance level, **1 % significance level, and ***0.1 % significance level.
Source: author.

^a Because *Box_office_p* is presented as a percentage, we algebraically transformed the volume attributes and the variables *Screen_no* and *Budget* into logarithmic form to eliminate estimation skewness.

horror movies with well-executed special effects can yield strong eWOM impacts that account for an increase in the contribution of revenue after the opening weekend to gross revenue.

6. Discussion: Sequential marketing of Maoyan and Douban

6.1. Comparison of Maoyan and Douban

According to our empirical results, Maoyan and Douban influence the gross box office revenue of movies, thereby supporting *H2a*. Volume on Maoyan is the main feature weighted in predicting a movie's gross revenue (Table 7). Specifically, when volume on Maoyan is greater, broadcast marketing is stronger for both low- and high-budget movies, which in turn leads to higher opening-weekend ticket sales. The high volume on Douban conversely leads to higher ticket sales after the opening weekend, suggesting the lagged effects of eWOM marketing.

Although valence has low power to predict gross revenue, it affects how revenue is distributed, that is, during versus after the opening weekend. Any increase in Douban (or Maoyan) ratings for a movie increases its popularity through lagged diffusion of eWOM and improves its box office performance after the opening weekend (Table 7). However, the magnitude of eWOM effects steadily decreases during a movie's theatrical release. Together, these findings support *H2b* and *H2c*.

As shown in Table 7, no considerable differences were found between the marketing modes of high- and low-budget movies. Both broadcast and eWOM modes are utilized to improve box office performance for high- or low-budget movies even if the latter much rely on social media diffusion to succeed. Hence, *H1* is rejected.

6.2. Sequential marketing confirmed

Although both Maoyan and Douban affect the box office performance of movies, they do so differently (Table 7, Fig. 7). Maoyan primarily operates in broadcast mode before a movie's release, whereas Douban features diminishing eWOM after the release. The two platforms follow a sequential process of marketing.

Because Maoyan is a ticket presale website, its volume indicates the perceived popularity resulting from the distributor's promotion before a movie's release. Douban has a reputation for being a social space for the cultural elite. Its volume and valence signify the experiences of this elite, which in turn can guide audiences. The willingness of moviegoers to watch a movie is higher when more Douban users comment on a movie and rate it highly during the movie's theatrical release.

Our empirical results can inform the marketing strategies used by movie distributors. Volume on Maoyan should be promoted before a movie's release, and volume and valence on Douban should be addressed after its release (Fig. 7). For high-budget movies such as Hollywood hits, attention should be specifically directed to the number of theatrical screens showing the films because it has the predominant influence on their gross revenue and the ticket sales after the opening weekend (Table 6, columns A and B). Their distributors should start screening movies in additional theaters when the volume or valence on Douban increases during the release.

7. Conclusion

In this study, we investigated Maoyan and Douban and their marketing effects on box office performance in China. With the RF tests, we first substantiated the effectiveness of Maoyan and Douban, proxied by their volume and valence, in upholding box office performance. The results of the polynomial regression further led us to discover distinct marketing modes on the two platforms. Marketing on Maoyan is primarily broadcast marketing before a movie's release, whereas that on Douban is eWOM after the movie's release.

Our literature review revealed inconsistent findings on the effects of

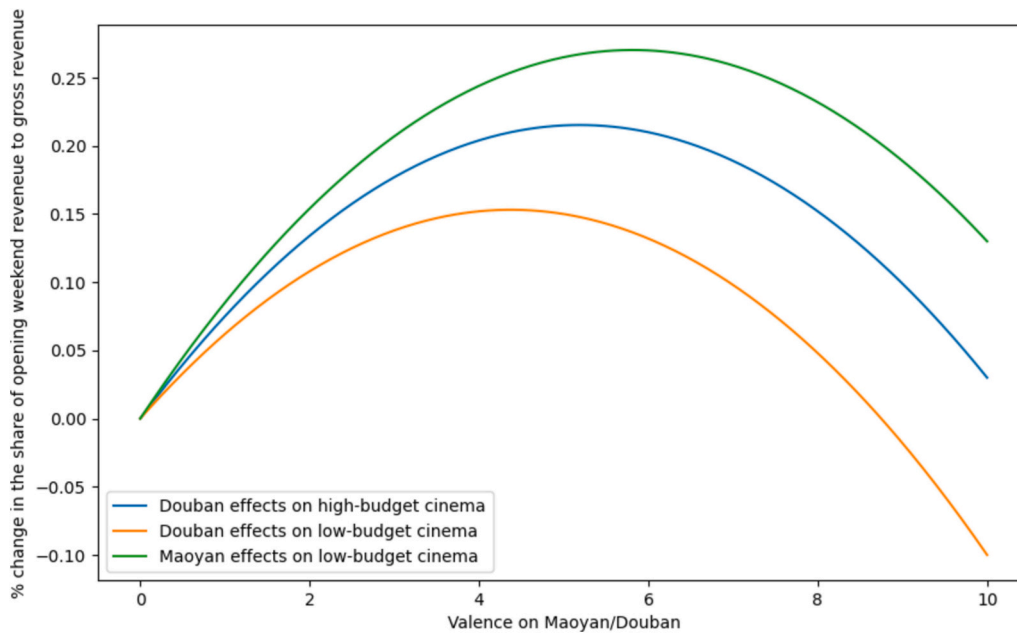


Fig. 6. The fitted lines of estimated quadratic effects.

Table 7
Comparison of Maoyan and Douban.

	HIGH-BUDGET movies	LOW-BUDGET movies
Maoyan volume	0.361 predictive power for gross box office revenue	0.693 predictive power for gross box office revenue
	<i>Broadcast Marketing</i> 0.082–0.083 % increase in gross revenue accounted for by the opening weekend revenue	<i>Broadcast Marketing</i> 0.052–0.056 % increase in gross revenue accounted for by the opening weekend revenue
Maoyan valence	0.018 predictive power for gross box office revenue	0.013 predictive power for gross box office revenue
	n.a.	<i>eWOM Marketing</i> 0.01 % decrease in gross revenue accounted for by the opening weekend revenue
Maoyan effects	0.379 predictive power for gross box office revenue	0.706 predictive power for gross box office revenue
Douban volume	0.044 predictive power for gross box office revenue	0.017 predictive power for gross box office revenue
	<i>eWOM Marketing</i> 0.072 % decrease in gross revenue accounted for by the opening weekend revenue	<i>eWOM Marketing</i> 0.045 % or 1.03e-06 % decrease in gross revenue accounted for by the opening weekend revenue
Douban valence	0.015 predictive power for gross box office revenue	0.004 predictive power for gross box office revenue
	<i>eWOM Marketing</i> 0.02 % decrease in gross revenue accounted for by the opening weekend revenue	<i>eWOM Marketing</i> 0.002 % or 0.009 % decrease in gross revenue accounted for by the opening weekend revenue
Douban effects	0.059 predictive power for gross box office revenue	0.021 predictive power for gross box office revenue

Source: author.

volume and valence attributes. In this study, we also addressed this inconsistency, highlighting volume as a prevalent feature for box office success. Structured numeric ratings were also confirmed to be a more effective proxy of valence than unstructured textual comments. Interestingly, no significant differences were found between the marketing modes of high-budget movies such as Hollywood hits and those of low-budget movies. Both were found to be affected by sequential marketing,

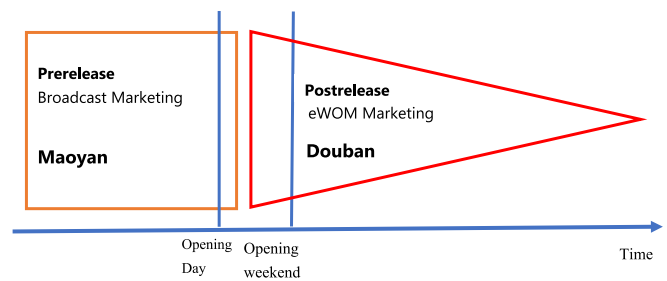


Fig. 7. The sequential marketing of Maoyan and Douban.

whereas low-budget movies primarily rely on digital marketing to succeed.

Most studies on Chinese film marketing have analyzed Weibo. Our research underscores sequential marketing in China and instead focuses on Maoyan and Douban. To our knowledge, this is the first study to investigate these video-specific social platforms, to define sequential marketing, and to differentiate between the marketing modes of Maoyan and Douban. Hollywood hit distributors are accordingly advised to address volume on Maoyan before a movie’s release, and volume and valence on Douban after its release. This study contributes to the field of film marketing, and future research could benefit from the original insights into sequential film marketing in China.

Our findings are applicable only to 2019 because COVID-19 had an influence on box office performance. Research should be conducted in the post-COVID-19 era to examine the marketing effects of social platforms during different periods. Future studies should also examine recently popular platforms such as WeChat and TikTok, compare their effectiveness, and validate our findings.

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CRedit authorship contribution statement

Yuntsai Chou: Writing – review & editing, Writing – original draft,

Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Wei Lin:** Visualization, Validation, Software, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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