An Investigation of Factors that Contribute to Movie Review Helpfulness in China

Yan Ou, Alton Y. K. Chua

Abstract—**This paper aims to study the factors contributing to movie review helpfulness in China. Using 2,197 movie reviews and 1,876 reviewers' information from the top 100 films released in 2020 on Douban.com, this paper mainly focuses on two types of features, namely, review-related factors (*Review Length*, *Review Timeliness*, *Review Extremity*, and *Review Reply*) and reviewer-related factors (*Reviewer Expertise* and *Reviewer Follower*). A zero-inflated-negative-binomial (ZINB) regression model is employed to examine the determinants of movie review helpfulness. Two main findings emerged. First, *Review Reply* was shown to be a significant factor in movie review helpfulness. Second, movie review helpfulness is highly associated with factors except for *Reviewer Expertise*.**

Index Terms—**Review helpfulness, movie reviews, Douban, ZINB model**

I. Introduction

Electronic word-of-mouth (WOM) is a means that connects the offline and online world and it bridges the gaps between the quality of products or services and customers' opinions [1]–[3]. As a type of eWOM, online customer reviews have become an invaluable reference source for prospective consumers [4], [5]. To cope with the problem of information overload caused by the massive number of online reviews [4], [6]–[8], potential consumers could look only for entries deemed as helpful by the online community[5].

Recent studies have paid attention to factors that might contribute to online review helpfulness. Some are review-related factors while others are reviewer-related [1]–[6]. Besides, since researchers' objectives and study contexts vary, other factors include membership tier [9], product reviews [10], and product rating [11], have also been identified.

Two types of goods based on customers' quest for the information of their quality are often distinguished: search goods and experience goods [12]. This paper focuses on online movie reviews, which are reviews of experience goods.

Although the factors for review helpfulness are well studied, three research gaps exist. First, results from prior studies have been inconsistent. For instance, while positive reviews are found to be more helpful than negative reviews [8], [12], [13], an entry's helpfulness increases when it has more negative words [4], [7]. Second, research on movie review helpfulness in China remains rare. Prior works rely largely on western review websites, including RottenTomato.com and IMDb.com. In contrast, China-based websites such as Douban.com which attract high internet traffic have not been used as datasets. Third, most mainstream Chinese movie review websites have a feature that allows users to reply to an existing movie review. This provision is missing from most western online movie review platforms [14]. To date, there has been limited research on the role of the reply function in online movie reviews [15].

For these reasons, this paper seeks to identify factors contributing to movie review helpfulness in China. It proposes and empirically tests a conceptual framework which contains review-related factors and reviewer-related factors [6], [8]. The review-related factors include *Review Length*, *Review Timeliness*, *Review Extremity*, and *Review Reply*. Reviewer-related factors contain *Review Expertise* and *Reviewer Follower*. Using 2,197 movie reviews and 1,876 reviewers' information from 100 movies in 2020 drawn from Douban.com, a zero-inflated-negative-binomial (ZINB) regression model is used to examine the association between the factors and helpfulness.

II. Literature Review

To ease navigation, many websites use an open-voting system by asking users if a given review is helpful and thereafter display all reviews according to the helpfulness votes garnered [7], [8], [16]. *Helpfulness Vote* is thus a quick indication of the value assigned by the online community to aid purchase decisions [17], [18].

A. *Review-related factors*

Review Length measures the amount of open-ended textual content the reviewer provides [13], [19], [20]. Prior studies have found the length of review to have a positive relationship with review helpfulness [9], [13], [21], [22]. However, lengthy reviews could lead to information overload, and thus are not deemed as helpful [11]. Therefore, this paper reexamines the relationship of *Review Length* and helpfulness and proposes the following research hypothesis:

H1: The length of a review is positively related to its helpfulness.

Review Timeliness refers to how timely a review is after the release of a movie [5]. Some studies argue that early movie reviews are more valuable in reducing the uncertainties of purchasing the movie ticket and would attract more customers [5], [8]. However, [23] finds that reviews published later could gain more helpfulness votes due to the display mechanism of the websites [24]. For example, most

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websites display reviews by date of submission, with the most recent reviews appearing at the top of the page. Thus, the second hypothesis is:

H2: The timeliness of a review is positively related to its helpfulness.

Review Extremity is associated with the star rating given by the reviewer, which can be positive or negative [8], [20]. For instance, in a five-star rating system, a one-star review shows extreme negativity while a five-star shows extreme positivity. As extreme reviews, both one-star reviews and five-star reviews are shown to have significant positive relationship with review helpfulness [5], [6].[21], [25], [26]. In contrast, [13] suggests that the extremity of reviews harms review helpfulness. Due to the inconsistency from the previous studies, we hypothesize:

H3: An extreme review is more likely to be helpful than a moderate one.

Review Reply or review comment refers to the number of replies a review attracts [27], [28]. The review-reply function can be found commonly in most mainstream movie review platforms in China [29] including Youku.com, Bilibili.com and Douban.com. It allows users to give feedback to the video contents and reply to users' comments or reviews. Such a feature is currently unavailable in mainstream Western movie review sites [14] and thus warrants investigation.

Some studies found that review replies could influence reviewer's motivation, satisfaction and increase the volume of review [30], [31]. *Review Reply* could be a proxy for the amount of interest generated by a review, and is therefore also considered an essential metric to *review popularity* [15], [32], [33]. According to information processing theory and hierarchy-of-effects model, review popularity is closely related to review helpfulness [34]. Thus, in the context of China-based movie review, we hypothesize that:

H4: Review reply is positively related to review helpfulness.

B. Reviewer-related factors

Reviewer Expertise indicates the extent to which the reviewer could write reviews with helpful information and of high quality [35]. The persuasive impact of *Reviewer Expertise* has been shown to be robust [35]. Some websites operationalize it as reviewer ranking. For instance, Yelp.com delivers the "Elite" badge [4], [11] and Amazon.com gives out the "Top 10,000 Reviewers" badge [35]. In other websites, it can be measured by the total number of previous reviews written by a reviewer [20], [36]. In general, expertise is found to be positively related with review helpfulness [6], [26], [35], [37]. Based on the literature above, we posit that reviews posted by reviewers with more expertise will garner more helpfulness votes. Thus,

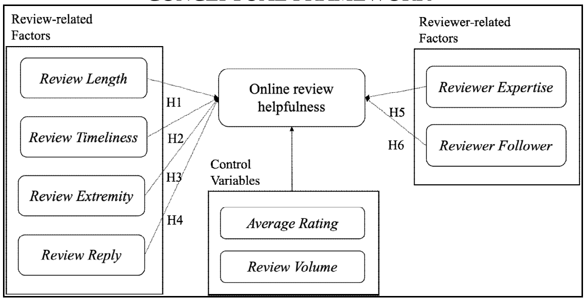
H5: Reviewer expertise is positively related to review helpfulness.

Within the reviewer characteristics, another critical factor that needs to be examined is the number of reviewers' followers. Based on the uncertainty reduction theory, when individuals encounter uncertainty, they will be motivated to seek for more information [38]. Previous studies found that the reviewers' follower number positively influences review helpfulness [22], [39] and that reviewers will be more motivated to write more helpful reviews to maintain their social standing [8]. As such, it is conceivable that a reviewer with more followers would post reviews with high quality [40], and thus attract more helpfulness votes:

H6: Reviewer follower is positively related to review helpfulness.

The control variables are adopted from [8]. *Average Rating* refers to the average rating given to movies by users. On Douban.com, movie's average rating is on a scale of 1 to 10. Another control variable is *Review Volume which* is the number of reviews a movie has been received up to the point of data collection.

FIGURE I
CONCEPTUAL FRAMEWORK



Based on the discussion above, the conceptual framework of this study is presented in Figure I.

III. Research Methods

The data is collected from Douban.com for three reasons. First, launched in 2005, Douban.com has become one of the most visited platforms for creating and sharing user-generated content[2], [41]. It is also the most comprehensive website for movie reviews in China compared to other websites such as Mtime.com and Maoyan.com [8], [14], [41], [42]. Second, due to the *Endowment Effect*, a movie's ratings on ticketing websites are higher than it should have [41]. Using the dataset from Douban.com could avoid this implicit bias. Third, Douban.com allows reviewers to disclose their personal information through a link their homepages for social reasons [8]. This enables reviewer-related data to be collected and studied.

The reviews on Douban.com come in two forms: a short review and a long review. The differences lay in three aspects. First, there is a 350 Chinese characters limitation in short reviews, but no such restriction is imposed on long reviews. Second, while users can cast only helpful votes to short reviews, they have the flexibility to cast either helpful or unhelpful votes to long reviews. This means long reviews can capture users' sentiments more completely. Third, users can reply directly to long reviews but not to short ones. Thus, data on *Review Reply* can be collected for analysis. Given that long reviews are unique to Douban.com but have been mostly ignored in previous studies [2], [6], [42], [43], this paper focuses specifically on long reviews (hereafter as movie reviews).

The dataset was drawn from 100 movies released in 2020 in Douban.com. All movies are on the hot list of the year, and would have attracted a critical mass of users, movie reviews and helpfulness votes [8], [36]. Due to the considerable review volume on Douban.com, and informed by prior research [5], the first 20 reviews of each movie with more than 10 votes were collected. Also, in order to study reviewer-related factors, reviewers' information of each review was collected.

The variables with descriptions in the study are listed in Table I. The dependent variable is review helpfulness which is operationalized as *Helpfulness Vote* provided by users [8], [9], [11], [35] and *Helpfulness Ratio* [16], [17], [19]. The characteristics of reviews and reviewers are the independent variable in this model.

TABLE I
DESCRIPTION OF VARIABLES

Variables	Descriptions
Dependent	
Helpfulness Ratio	The number of helpfulness votes cast divided by the total number of votes
Helpfulness Vote	The number of helpfulness votes given by users up to date.
Independent	
Review Length	The number of valid Chinese characters in the review.
Review Timeliness	The absolute value of the interval between the earliest movie release date and review date.
Review Extremity	Dummy variables of 1 and 0: if the rating of review is 1 or 5, it is considered as 1 and 0 if the rating is 2,3 or 4.
Review Reply	The number of replies a review obtained up to the data retrieved date.
Reviewer Expertise	The reviewer's total number of movie reviews up to the data retrieved date.
Reviewer Follower	The total number of followers of a reviewer up to the data retrieved date.
Control	
Average Rating	The movie's average rating on a scale of 1 to 10.
Review Volume	The number of reviews a movie has been received up to the data retrieved date

We chose models in the zero-inflation family for two reasons. First, the dependent variable, *Helpfulness Vote*, is a count variable with many zeros (20%) and of high dispersion. When the dataset has a high fraction of zeros and is significantly skewed, traditional ordinary least squares regression is not preferred [43]. Models in the zero-inflation family can address both overdispersion and excessive zeros issues [35], [44]. The other reason is that the models in the zero-inflation family could explain not only non-zero counts but also zero counts. It explains why a movie review received helpfulness votes and, at the same time, clarifies why it did not receive any votes.

IV. Results

The descriptive statistics are presented in Table II. The variance inflation factors (VIFs) were less than the threshold of 5 [44]. This indicates no significant multicollinearity issue between independent variables

The regression results are listed in Table III, an overdispersion test is provided. The result shows that the dependent variable, namely, *Helpfulness Vote* is significantly over-dispersed, thus confirming that ZINB was a more appropriate option compared to Zero-Inflated-Poisson model.

Two models are presented in Table III. The Count Model section presented on the left is for non-zero counts of helpfulness vote. The hypotheses are tested in this section: the hypothesized path from *Review Length* to review helpfulness is positive (β=1.043e-4, p<0.001), indicating the support of H1. *Review Timeliness* is negatively related with helpfulness vote (β=-6.576e-4, p<0.001), which supports H2, even though the correlation is weak. The relationship between *Review Extremely* and review helpfulness is also significantly positive (β=0.2636, p<0.001), thus H3 is supported. The value of *Review Reply* (β=0.8649-1, p< p<0.001) confirming that H4 is supported. The value of *Reviewer Expertise* (β=-0.02207, p<0.1) shows a negative but less significant correlation with the dependent variable, offering insufficient evidence to support H5. The value of

TABLE II
DESCRIPTIVE STATISTICS

Variables	Mean	Std. Dev	Min	Max	VIF
Dependent					
Helpfulness Ratio	0.71	0.38	0.00	1.00	
Helpfulness Vote	99.04	432.13	0.00	12821.00	
Independent					
Review Length	1232.63	1436.95	0.00	24489.00	1.255
Review Timeliness	93.85	111.55	0.00	466.00	1.223
Review Extremity	0.29	0.45	0.00	1.00	1.023
Review Reply	34.04	147.93	0.00	2616.00	1.251
Reviewer Expertise	733.98	1044.68	0.00	10549.00	1.122
Reviewer Follower	3571.90	12517.96	0.00	158359.00	1.183
Controls					
Average Rating	6.58	1.34	3.10	9.50	1.167
Review Volume	486.06	922.82	21.00	5702.00	1.437

TABLE III
ZINB REGRESSION RESULTS

Variables	Count Model		Zero-inflation Model	
	β	P	*β*	P
Constant	-5.768e-2	0.568	2.684	<0.001
Independent				
Review Length	1.043e-4	<0.001	-4.840e-4	<0.05
Review Timeliness	-6.576e-4	<0.001	0.007	<0.001
Review Extremity	0.2636	<0.001	-0.675	<0.01
ln(*Review Reply*)	0.8649	<0.001	-2.273	<0.001
ln(*Reviewer Expertise*)	-0.02207	<0.1	0.065	<0.5
ln(*Reviewer Follower*)	0.1154	<0.001	-0.235	<0.001
Control				
Average Rating	0.1317	<0.001	-0.399	<0.001
Review Volume	7.229e-5	<0.001	-0.011	<0.001

Overdispersion Test	Chi-Square	P
	77740.574	<0.001

Reviewer Follower (β=0.1154, p<0.001) lends support for H6.

The Zero-inflation Model section on the right is for the zero counts of *Helpfulness Vote*, that is, to test what would cause zero helpfulness vote. *Reviewer Expertise* (β= 0.065, p<0.5) shows no correlation with the zero-helpfulness vote. The results are consistent with the Count Model.

V. Discussion

This study investigates the factors that influence the helpfulness of movie reviews in the context of the Chinese

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movie market using reviews from Douban.com. There are three key findings. First, a review written by a more experienced reviewer might not necessarily attract helpfulness votes. Two possible explanations are proposed: one reason is the design of the platform. Unlike Yelp.com or Amazon.com, Douban.com does not offer any reviewer ranking system. A user only sees the number of reviews a reviewer posted after clicking the reviewer's profile picture. Without any visible display of the reviewers' metadata, the persuasive effect of communication skills [35] is lost. The other reason is the measurements of *Review Expertise*. In this study, we used the total number of movie reviews written by the reviewer as the *Review Expertise*, but the conception of *Review Expertise* could be measured multidimensionally.

Second, the new variable adopted in this study, *Review Reply*, was found to have a significant positive relationship with review helpfulness. *Review Reply* may play a particularly essential role since it conveys attention, co-presence, and participation in the shared experience [30]. Whether the review is positive or negative or controversial, users express their opinions and exchange ideas about the movie when they post replies to the review. More replies are indicative of the level of interest. As a platform, Douban.com hopes to increase users' activity on its site. Increased levels of user interaction usually lead to higher profitability [14]. *Review Reply* could also increase the volume of reviews, for it boosts reviewer's motivation and satisfaction [30], [31], and users could gain additional perspectives by browsing both movie reviews and replies.

Third, this study not only considers the factors that affect helpfulness vote but also adopts another approach by employing the ZINB model to analyze the factors of zero helpfulness vote. As summarized, if a movie review is written by a reviewer with less follower and the review is short, not timely, with a moderated rating, receiving fewer replies, this review will be more likely to get zero helpfulness vote, and the numbers of reviews a reviewer posted might not influence the votes.

VI. Conclusion

This study investigates the factors that influence the helpfulness of movie reviews in the context of the Chinese movie market using reviews from Douban.com. The proposed conceptual framework contains six factors, namely,

Review Length, Review Timeliness, Review Extremity, Review Reply, Reviewer Expertise and Reviewer Follower. The first four are review-related while the last two are reviewer-related factors.

From the analysis, two key findings emerge, First, in line with previous studies, all of the variables, except Reviewer Expertise in the conceptual framework were found to contribute to movie review helpfulness. A movie review, that is longer [4]–[6], [13], [19], [45], timely [5], [9] with a more extreme rating [5], [6], has more replies and the reviewer who wrote the review has more followers [8] will be more likely to gain helpfulness votes. What is surprising is that a review written by a more experienced reviewer might not necessarily attract helpfulness votes. Two possible explanations are proposed: one reason is the design of the platform. Unlike Yelp.com or Amazon.com, Douban.com does not offer any reviewer ranking system to help users better know the expertise of the reviewers. A user could only click the reviewer's profile picture to view the number of reviews he or she posted. When a user only sees the review, the persuasive effect of communication skills [35] is lost. The other reason is the measurements of Review Expertise. In this study, we use the total number of movie reviews written by the reviewer, but the conception of Review Expertise could be measured multidimensionally.

Second, the new variable adopted in this study, Review Reply, was found to have a significant positive relationship with review helpfulness. Review Reply may play a particularly essential role in channels where people seek social attention and validation since they might convey attention, co-presence, and participation in the shared experience [30]. It can be used as a proxy to measure the helpfulness of a review, which is the condition of review popularity [34]. Whether the review is positive or negative or controversial, users express their opinions and exchange ideas about the movie when they post replies to the review. Different groups can view such discussions from different perspectives, resulting in the movie review receiving more helpfulness votes. Moreover, more replies might indicate that more users are involved. As a platform, Douban.com hopes to improve its users' "activity" on the site. Increased levels of user interaction usually lead to higher profitability [14]. Review Reply could also increase the volume of reviews, for it boosts a reviewer's motivation and satisfaction [30], [31], and moviegoers could retrieve helpful advice and deeper understandings on movies when browsing both movie reviews and replies.

In terms of theoretical contributions, this study represents one of the few studies that examines the role of Reviewer Follower and Reviewer Expertise in influencing helpfulness votes [8]. A more thorough investigation of review and reviewer characteristics would be a significant step forward in the development of the literature on review helpfulness. Second, the empirical evidence complements prior findings by illustrating the factors that contribute to reviews with zero helpfulness vote. Douban.com does not highlight the movie volume a reviewer has, thus invalidating the persuasive impact of Reviewer Expertise. Third, Review Reply was shown to be another significant contributor to review helpfulness. This further deepens our understanding of the helpful movie reviews. Apart from theoretical significance, this study also holds practical implications. First, the findings of this study can be used by UGC platforms to strengthen their incentive mechanisms and guide users to submit more helpful reviews. Secondly, since the research found a significant positive relationship between Review Reply and review helpfulness, UGC platforms can consider implementing the reply function on the platform. Thirdly, the findings could equip both movie critics and platform users with more practical knowledge on how to write a helpful review.

This study also has some limitations. First, the dataset was crawled in Douban.com in China; the results might not apply to other platforms such as Mtime.com or BiliBili.com in China. They both hold long and short movie reviews that have been rarely studied. Future work can study those platforms based on the findings of this paper. Second, the content of the reviews was not investigated. Linguistic features such as readability, and visibility of the reviews can also be essential factors for review helpfulness [46]. Furthermore, this study focused solely on a specific category. Additional review and reviewer-related determinants should be taken into consideration—for example, movie genre, movie languages and the countries of movie origin. Further research could consider these variables.

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