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Sponsorship disclosure and consumer engagement: Evidence from Bilibili video platform☆

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ABSTRACT

With the rapid advancement of mobile internet, UGC video platforms have become integral to the daily lives of young generations. For content creators on these platforms, sharing videos sponsored by corporations is the primary method to monetize their work. This research delves into the impact of video content sponsorship and sponsorship disclosure on consumer engagement by analyzing nearly 30,000 videos on the Bilibili platform. The results indicate that video sponsorships have a significantly negative impact on consumer engagement. However, comprehensive disclosure of sponsorship beforehand can improve consumer engagement. Additionally, our study demonstrates that followers of top-tier content creators are more sensitive to video sponsorships. This paper presents a critical empirical investigation of the sponsorship issue within the context of UGC platforms, making valuable contributions to the theories of advertisements' externalities in two-sided markets and information asymmetry.

1. Introduction

With the rapid development of telecommunications infrastructure, especially with the advancements to the fourth and fifth generations, the mobile internet industry has experienced an unprecedented boom. This growth encompasses various sectors such as social media, e-commerce, food delivery, and online video streaming. As a result, discussions about consumer engagement issues on these

☆ This paper contributes significantly to the existing literature in three key theoretical aspects. Firstly, it provides substantial empirical evidence on sponsored content, specifically focusing on consumers' responses to the content itself and conducting comprehensive testing of the impact of prior-disclosed sponsorship. This fills an important gap in the research and enhances our understanding of how consumers react to sponsored content. Secondly, the study adds to the understanding of advertisements' externalities on two-sided platforms. Traditionally, platforms have employed strategies like scheduling advertisements displacement to mitigate negative effects (Bhargava, 2022; Kumar et al., 2020; Sun et al., 2017). However, in the context of UGC platforms, our empirical analysis explores the effect of prior-disclosure of sponsorship on consumer engagement and finds a positive outcome. Prior-disclosure makes uploaders appear more genuine, thereby reducing the negative externalities of advertisements. This result highlights the disclosure of advertising information as an effective tool for ads management. Thirdly, the paper sheds light on the theories of information asymmetry and information disclosure policy. While existing theories and empirical work have primarily focused on changes in utilities for both sides of the market (Akerlof, 1978; Spence, 1978), our study instead concentrates on their emotional effects, as characterized by further engagement. The empirical results demonstrate contrasting effects of information asymmetry and information disclosure, with the influence varying among influencers with different levels of popularity.

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online platforms have become widespread in literature. Consumer engagement, as a concept, is seen as a reflection of consumers' attitudes and is demonstrated through actions like "liking," "favoriting," commenting, or sharing content (Liadeli et al., 2023). Researchers have identified factors such as advertisements, poster characteristics, and platform strategies as influencers of consumer engagement (Khan et al., 2016; Liadeli et al., 2023; Santos et al., 2022). Most of the previous literature on consumer engagement has primarily focused on social media platforms. However, in recent times, video platforms, especially User-Generated Content (UGC) platforms, have gained significant importance in our daily lives and have garnered extensive academic attention (Rong et al., 2019; Bhargava, 2022; Ye et al., 2022). UGC platforms have a more interactive and visual nature, providing an essential context for further exploring the problem of consumer engagement.

There are two main types of video platforms: UGC (User-Generated Content) platforms and PGC (Professionally-Generated Content) platforms. Video platforms like Bilibili and Douyin are typically categorized as UGC platforms, which differ from PGC platforms (Daugherty et al., 2008). UGC platforms are characterized by content primarily provided by ordinary users rather than professional institutions, with examples like Facebook, YouTube, and MySpace (Lu and Stepchenkova, 2015). In China, UGC video platforms, particularly Bilibili, have witnessed significant growth in recent years. For instance, Bilibili's monthly active users (MAUs) have surged from 77.5 million to 326 million in just five years, making it one of the most popular UGC video platforms among young generations (see Fig. 1). As such, UGC video platforms provide a crucial context for exploring consumer engagement in new and innovative ways.

While the rapid development of UGC platforms was remarkable, it also posed a challenge to both platforms themselves and content providers, which is the difficulty in finding potential monetization channels. Traditionally, in video marketing and media communication, PGC video platforms were applied, especially for creating institutional content (Erviti et al., 2020), and pre-movie advertisements were the main source of financial support, which might reduce views in the first place (Bhargava, 2022; Dehghani et al., 2016) (see Fig. 2). However, some UGC platforms nowadays have committed to not introducing any pre-movie advertisements to protect user experience.

To address the absence of pre-movie advertisements, sponsored content embedded within each video has emerged as an alternative means of financial support. Various types of sponsored content, such as native advertising, influencer marketing, and embedded advertisements, have been extensively discussed in existing literature (Mathur et al., 2018; Beckert et al., 2020). Previous studies have explored the impact of sponsored content on consumer behaviors (Muller and Christandl, 2019; Kim and Kim, 2021), and sponsorship disclosure has also been a topic of examination, yielding controversial results (Stubb et al., 2019; Boerman et al., 2017). However, sponsored content embedded in UGC remains a relatively new business model, requiring empirical evidence to better understand its effects and the impact of sponsorship disclosure.

Prior literature has primarily focused on consumer responses to sponsored brands, but our research shifts the focus to examine their responses to the content itself and sequential engagement behavior, highlighting the user co-governance characteristic of UGC platforms when compared to PGC platforms. Moreover, few studies have explored the impact of prior disclosure, which involves revealing sponsorship information outside of the video content itself. To address these gaps in knowledge, this paper aims to answer the following research questions: What are the effects of sponsored content and prior information disclosure of sponsored content on consumer engagement?

In this paper, we focus on Bilibili, one of the most popular UGC video platforms in China, known for its representative sponsored content. Sponsored content on Bilibili is referred to as "Qia Fan Video", which content creators generate to monetize their online web traffic (Liu, 2022). Essentially, "Qia Fan Video" serves as a form of advertisement, where advertisers pay influential content creators on Bilibili in exchange for their originally produced video clips that implicitly or explicitly promote the products or services of the sponsor (Wu, 2021). The platform typically takes a portion of the advertising fees as commission for its role as an intermediary.

It's worth noting that there are various forms of sponsored content on Bilibili, with two main types being "pre-informed sponsored content" and "uninformed sponsored content" (Liu and Sun, 2021; Casale, 2015). "Pre-informed sponsored content" refers to video clips that inform potential viewers about the advertising content within the video through various channels, such as video titles, video tags, information about co-creators, etc. (see Fig. 3). Examples of "pre-informed sponsored content" could include sponsor information in the title or co-creator column, or in more explicit cases, stating "This is an advertisement" in the title. Two examples of "pre-informed sponsored content" are provided below:

The other type of sponsored content discussed in this paper is "uninformed sponsored content." This type of sponsored video clip

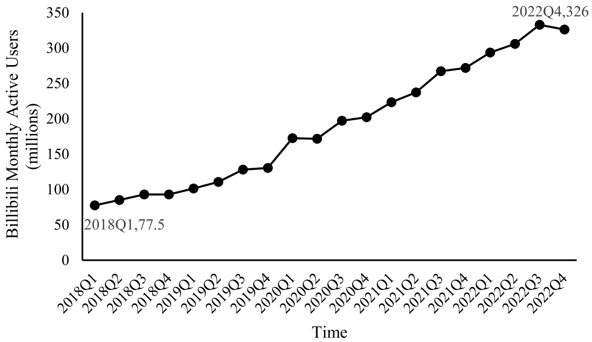

Fig. 1. Booming MAUs on Billibili.

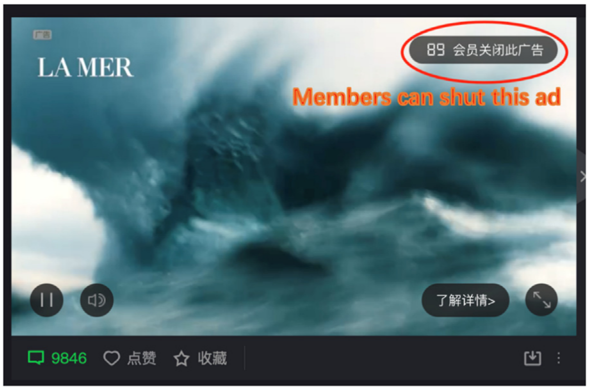

Fig. 2. Traditional pre-movie advertisement.

Fig. 3. Pre-informed sponsored content.

does not provide any visible information about its advertising nature to viewers before they click and watch the video content. As a result, viewers cannot differentiate between "uninformed sponsored content" and original content without advertising prior to watching the content. Two examples of "uninformed sponsored content" are provided (see Fig. 4).

To examine the impact of video content sponsorship and sponsorship disclosure on consumer engagement, this study utilizes regression analyses based on data from 30,000 videos on the Bilibili platform. The effects of sponsorship are found to vary among influencers with different levels of popularity. To address potential endogenous issues, instrumental variable regression is employed. The paper makes significant theoretical contributions by shedding light on the externalities of advertisements on two-sided platforms and demonstrating that the disclosure of advertising information can serve as an effective tool for ads management. It also delves into the theories of information asymmetry and information disclosure policies, focusing on their emotional effects as manifested in

Fig. 4. Uninformed Sponsored Content (informed at the end of the video).

consumer engagement behaviors. Additionally, this study offers valuable empirical evidence for the literature on sponsored content, with a particular emphasis on consumers' responses to the content itself and a thorough examination of the effect of prior-disclosed sponsorship. In terms of practical implications, the findings of this research offer strategic guidance for both content uploaders and platforms. These insights can help content creators and platforms better understand how to navigate sponsorship arrangements and optimize consumer engagement.

The remainder of this paper is organized as follows: Section 2 reviews existing literature related to sponsored content and other theories, Section 3 proposes hypotheses based on existing theories, Section 4 reports summary statistics of the data and performs empirical tests, including robustness tests and heterogeneity analysis. Finally, a brief conclusion on our findings is provided.

2. Literature review

2.1. Sponsored content and sponsorship disclosure

Existing literature has extensively explored the impact of sponsored content on consumer behavior. On the positive side, well-executed ads that seamlessly integrate within the video flow can effectively capture viewers' attention and evoke emotional connections. Kim and Kim (2021) found that consumers responded more positively to sponsored content that demonstrated a high level of influencer-product congruence. However, on the negative side, advertisements can also disrupt the viewing experience, leading to ad avoidance behavior and generating negative perceptions. Muller and Christandl (2019) employed a serial mediation model to investigate various marketing campaigns in the gaming industry and revealed that sponsored content tended to elicit more negative responses from consumers when compared to other marketing methods.

Furthermore, some studies have investigated the concept of sponsorship disclosure and its effect on consumer behavior and advertising performance, yielding conflicting results. Mathur et al. (2018) reviewed content on YouTube and Pinterest and observed that only 10% of sponsored content adhered to FTC rules regarding disclosing sponsorship to consumers. On the positive side, Stubb et al. (2019) found that sponsored content with sponsorship compensation justification disclosure generated more positive responses from consumers. Kay et al. (2020) compared the advertising performance of macro and micro social media influencers and found that sponsoring micro-influencers produced better advertising performance, and sponsorship disclosure improved consumer attitudes towards brands. However, the study's results may not be generalizable because the experiment used four artificial influencer accounts on Instagram. Beckert et al. (2020) discovered that while sponsorship disclosure increased consumers' perception of the content's persuasion intent, it did not necessarily lead to their disapproval of the sponsor's brand.

Conversely, some research suggests that sponsorship disclosure has a negative effect. Boerman et al. (2014) found that disclosing sponsorship for sponsored content on TV generated negative responses from consumers. Boerman et al. (2017) discovered that disclosing sponsorship for sponsored content on Facebook created a sense of mistrust among consumers and dampened the effect of electronic word of mouth. Wojdynski and Evans (2016) found that using words like “sponsored” and “ad” within sponsored content elicited negative attitudes from consumers. Hwang and Jeong (2016) revealed that a “simple” form of sponsorship disclosure negatively impacted consumer attitudes, while a detailed and honest disclosure of sponsorship by influencers could mitigate some of the negative effects. Lee et al. (2018) found that directly informative content containing product price information significantly reduced consumer engagement with the content on Facebook. Most of these studies were based on the Persuasion Knowledge Model, which suggests that content with persuasion intent causes consumer aversion.

Overall, existing literature has extensively discussed the influence of sponsorship disclosure on consumer attitudes towards sponsor brands, but little attention has been paid to the effect of sponsorship disclosure on consumers' response to the content itself. Moreover, the concept of prior-disclosure of sponsorship, which refers to disclosing sponsorship information before watching the video content, has not been thoroughly covered in existing literature. Therefore, this paper aims to address this gap by examining the effect of prior-disclosure of sponsorship on consumer responses to video content.

2.2. Externality of advertisements in two-sided markets

This paper contributes to the literature on two-sided market theory and the negative externality of advertisements on such markets (Anderson and Jullien, 2015; Rochet and Tirole, 2004; Armstrong, 2006), with a specific focus on the prominent two-sided video platform Bilibili (Rong et al., 2019). In a two-sided market, cross-side network effects imply that different user groups can have varying impacts on each other. While buyers and sellers create positive interactions, advertisers are believed to introduce negative network effects to the other user groups (Ye et al., 2022). Advertisers seek to gain access to more consumers, but this approach can potentially diminish consumer satisfaction as advertisements are typically “bundled” with services or products (Armstrong, 2006). Despite extensive discussions about the negative externality of advertisements on media platforms, there is limited empirical evidence regarding the actual impact of advertising on consumer behavior. Some studies support the notion that advertisements on TV media may reduce the amount of time consumers spend watching a channel (Wilbur, 2008), while others suggest that consumers may not dislike advertisements as much as commonly believed (Kaiser and Song, 2009). With the rise of the internet and new advertising formats, the attitudes of consumers towards sponsored content remain an area of exploration.

In the case of advertising generating negative externality on online two-sided markets, existing literature has discussed ad management tools that may mitigate the side effects and lead to a win-win outcome. For instance, better matching of advertisements can reduce consumers' distaste (Bhargava, 2022). The platform utilizes its matching technology to target ads as accurately as possible to consumers' interests, which might, in turn, pique consumers' interest and reduce their dissatisfaction. Another tool is finding the optimal timing for advertisements displacement (Kumar et al., 2020). Users' engagements are monitored by the platform, and the advertisements should be displaced the instant the engagement reaches a certain level. For In-APP fading ads, the optimal sequence of the ads will be determined to maximize the platform's revenue (Sun et al., 2017). Existing literature mainly explores the schedule of advertisements displacement and focuses on platform strategies. However, in the context of UGC platforms, advertising takes on a new dimension. Whether the information of advertising is disclosed or not (Boerman et al., 2014; Wojdynski and Evans, 2016; Lee et al., 2018) becomes a crucial factor affecting consumers' attitudes towards user-generated content and, consequently, influencing the revenue of this two-sided market. In our work, we empirically analyze whether the disclosure of advertising information becomes an effective ads management tool.

2.3. Information asymmetry and optimal information disclosure

This paper relates to the classic theory of information asymmetry (Akerlof, 1978; Spence, 1978) as it aims to examine the impact of prior sponsorship disclosure on consumer behavior. Information asymmetry can lead to inefficiencies, like in the "lemon market," where the side without information has a biased belief about the true type of the other side (Akerlof, 1978). To alleviate this problem, various information policies can be adopted, including signaling (Spence, 1978), mechanism design (Myerson, 1989), Bayesian persuasion (Kamenica and Gentzkow, 2011), etc. All of these strategies revolve around when and how to disclose information to induce a better outcome. Theories on information disclosure suggest that limited disclosure by information senders would maximize sender profit, while full disclosure would maximize receiver utility (Lizzeri, 1999; Rayo and Segal, 2010). Dynamic disclosure policies, finding the optimal timing to disclose information, will also lead the receivers' actions to maximize the senders' utilities (Renault et al., 2017; Ely and Szydlowski, 2020). In the context of platform economies, research explores second-hand trading platforms like eBay and Zhuanzhuan (Lewis, 2011; Rong et al., 2022), which have found that certain levels of information disclosure increase the probability of transactions.

Previous theories and empirical work on information asymmetry mainly focused on the change in utilities of both sides of the market and explored the sequential actions of the receivers for the purpose of maximizing their own utilities after the information disclosure policy. However, it remains underexplored whether information disclosure will influence receivers' attitudes or emotions. In the context of UGC video platforms, information asymmetry exists between content creators and consumers, as the former knows whether the video contains an advertisement or not, while the latter is unaware until after watching the video, unless the information is disclosed beforehand through video titles, tags, or other channels. Besides, the "likes," "coins," and "shares" of each video are the best reflections of viewers' attitudes. In this way, this study innovatively explores the emotional effect of information asymmetry as well as the information disclosure strategy in the context of online video platforms.

3. Hypotheses development

Based on existing literature, we propose two research hypotheses.

3.1. Sponsored content and consumer engagement

The primary objective of this paper is to investigate whether sponsored content has a negative impact on consumer engagement compared to user-generated content on Bilibili, a popular online platform. It is widely believed that consumers are less inclined to engage with sponsored content primarily due to their aversion towards advertisements. This assumption aligns with the persuasion knowledge model (Friestad and Wright, 1994) and the negative externality effects (Armstrong, 2006), providing valuable insights into the potential decrease in consumer engagement levels when exposed to sponsored content.

The persuasion knowledge model suggests that consumers possess a cognitive understanding of advertising tactics and develop an awareness of persuasive attempts made by marketers. According to this model, consumers may perceive sponsored content as a deliberate attempt to influence their behavior, leading to a defensive response characterized by reduced engagement. For instance, in the context of social media, sponsored content created a sense of mistrust among consumers and dampened the effect of electronic word of mouth (Boerman et al., 2017). In this way, content with persuasion intent causes consumer aversion.

On the other hand, the negative externality effects highlight the unintended consequences of advertising on user-generated content. It posits that the presence of sponsored content alongside user-generated content creates a negative spillover effect, diminishing the overall engagement levels within a given context. Evidence can be found in the decline of consumer satisfactory responses and the time they spend watching the sponsored videos (Armstrong, 2006; Wilbur, 2008). These suggest that the negative externalities arising from sponsored content, such as consumers' aversion towards advertisements and the potential spillover effect on user-generated content, contribute to a decrease in consumer engagement levels.

H1. Sponsored content will have lower consumer engagement compared to user-generated content due to the negative externalities associated with advertisements.

3.2. Sponsored content disclosure and consumer engagement

The second question that this paper aims to address is whether prior-disclosure of sponsorship has an impact on consumer engagement. Before delving into the details, it is necessary to explain the process of watching a video on Bilibili. Essentially, there are three steps that a consumer goes through to watch a particular video clip. First, the consumer browses through a video feed interface that contains information on various videos, including titles, front pages, and uploaders. Second, the consumer decides whether to click on a video based on the information presented. Upon clicking on a video, the consumer is taken to a webpage that provides more detailed information about the video, such as tags and co-creators. Finally, after watching the video clip, the consumer may choose to "like," "save," "share," or comment on the video.

There are mainly two types of sponsored content on Bilibili: one with prior-disclosure of sponsorship and one without. Sponsored content with prior-disclosure of sponsorship informs consumers about the sponsorship through video titles, tags, and co-creators, allowing consumers to receive the sponsorship information before watching the content. Therefore, we can identify the difference in consumer engagement between these two types of sponsored content.

Existing theories produce conflicting predictions regarding this effect. According to the persuasion knowledge model, some studies have suggested that the disclosure of sponsorship would increase the persuasive intent of the video content, thereby reducing the level of consumer engagement (Boerman et al., 2014). Others argue the opposite, suggesting that disclosure of sponsorship would make the uploader appear more genuine, thereby reducing the persuasive intent of the video (Stubb et al., 2019). Theories on information disclosure, however, support the latter effect. The rationale is that prior-disclosure of sponsorship would reduce negative externalities and make the "market" more efficient by preventing consumers who find the opportunity cost of watching a video with sponsored content too high from watching the content in the first place. Specifically, a consumer forms an expected return of watching a certain video clip based on all the prior-disclosed information, such as titles and front pages. The consumer will only choose to watch the video if the expected return is higher than the opportunity cost of engaging in other types of entertainment, such as playing video games. Thus, if the realized return of watching the video turns out to be lower than the expected return due to unexpected sponsored content, the consumer's welfare will be affected, reducing their intent to "like" the video.

In all, we propose the following hypothesis regarding this question based on our previous discussion::

H2. Sponsored content with prior-disclosure of sponsorship will have a higher level of consumer engagement compared to undisclosed sponsored content.

4. Data and descriptive statistics

4.1. Data

We utilize a distinctive dataset of 30,000 videos from the Bilibili platform to examine the correlation between sponsorship disclosure and consumer engagement. As previously mentioned, Bilibili is among the most popular UGC video platforms in recent years, attracting millions of content creators who monetize their online traffic through sponsored content known as "Qia Fan Video." This sponsorship enables numerous full-time "Uploaders" (active content creators) to thrive on the platform. To cater to the monetization demands of these "Uploaders," Bilibili offers specialized services called "Huahuo," which acts as an intermediary between "Uploaders" and sponsored brands. However, "Huahuo" only serves "Uploaders" who have completed real name authentication, released original videos within the last 30 days, and have more than 10,000 followers. Currently, there are approximately 13,000 ″Commercial Uploaders" with over 10,000 followers on the Bilibili platform. Moreover, the platform's features, such as liking, coin dropping, bullet screen, and comments, facilitate better interactions between viewers and "Uploaders." The vast number of content providers on the platform, along with the various interactive behaviors, have provided a rich and unique dataset for this study.

4.2. Methodology

The data for this study was collected by crawling the official website of Bilibili. Initially, we gathered key information on all "Commercial Uploaders", such as their number of followers, unique account ID (uid), account name, video category, and whether they have signed with an MCN, among other relevant details. Due to the sheer volume of data, we conducted stratified sampling to select content providers and their videos for analysis. Specifically, we divided "Commercial Uploaders" into three layers based on their number of followers, namely "Elite" (with more than 1 million followers), "Mid-tier" (with 100 thousand to 1 million followers), and "Micro" (with less than 100 thousand followers). We then used the Neyman allocation method for random sampling and selected a total of 1000 ″Uploaders", including 432 ″Elites", 486 ″Mid-tiers", and 82 ″Micros".

After collecting 1000 samples of "Uploaders", we gathered data on 30 recently released videos from each of them. The video data includes views, bullet chats (also commonly referred to as "danmaku"), release date, likes, coins, saves, shares, comments, text of comments, and text of bullet chats. Subsequently, we conducted keyword searches on the text information of comments and bullet chats. Given that Bilibili has a unique bullet chatting culture, users usually express their opinions about sponsored content in comments and bullet chats. Based on our experience, we used typical words in bullet chats and comments that reflect users' reactions to sponsored content, such as "Qia Fan," "Advertisements," and "Sugar Daddy" as keywords. We then categorized videos with these keywords as "sponsored videos", and vice versa. Additionally, as users often express their surprise in comments or bullet chats while watching "unannounced sponsored videos," we further categorized videos with the term "unprepared" in bullet chats as "unannounced sponsored videos," and vice versa. It should be noted that due to the limited research on the Bilibili platform in existing literature, the selection of keywords is solely based on our experience and may not cover all possible keywords.

Due to the significant amount of data and the anti-crawler technology employed by the Bilibili platform, the data collection process lasted almost a month, from February 19th to March 15th, 2022. In the end, we obtained 29,918 video data, with the exception of some missing data, such as the New Year activity video released by the platform. This video is neither an original video nor a "sponsored video," and its data structure differs from others, so we treated them as outliers and dropped the data.

4.3. Summary statistics

As mentioned previously, the data we collected from the Bilibili platform can be divided into three categories: interactive information of videos, including views, likes, coins, shares, and other indicators; information of "Uploaders," including followers, account ID, and categories; and advertising information of videos, including whether the video is an advertisement and whether the advertisement is notified in advance. To provide a visual representation of what these variables refer to, we have included Figs. 5–7 below. Additionally, please refer to Table 1 for the detailed meanings of all the variables.

We also show the detailed descriptive statistics for all variables in Table 2.

5. Variables and regression model

5.1. Variables

The variables used in the empirical analysis have significantly different scales, therefore we will take natural log of the variables with large magnitudes.

5.1.1. Dependent variable

In this paper, we employ standard metrics provided by the Bilibili platform to measure consumer engagement with video content as the dependent variable. There are several metrics available, including likes, coins, saves, shares, comments, bullet chats, and more. For our benchmark regression model, we will initially use "coins" as the dependent variable because it possesses unique properties that other metrics do not have. We will consider using other metrics for the robustness test section.

The "coins" metric is an exclusive feature on the Bilibili platform. It represents a virtual asset that users possess, and giving coins to a video deducts an equivalent number of coins from the user's account. Apart from supporting videos through giving coins, users can also use coins to purchase other value-added services on Bilibili, such as decorations, etc. However, coins cannot be directly purchased with money. To qualify for obtaining coins, a user needs to pass an exam and verify their account with a mobile phone number. Coins can be obtained through various activities, such as staying online or uploading videos, and 10% of the total coins received by videos will be distributed to the uploaders.

In summary, coins are limited resources, making them a more representative and robust measure of consumer engagement. This is because coins are less susceptible to manipulation compared to other metrics such as "likes" and "shares", which can be artificially inflated through click farms on the internet (Rong et al., 2022). Therefore, we use coins as the dependent variable in our benchmark model to ensure a reliable and meaningful assessment of consumer engagement on the Bilibili platform.

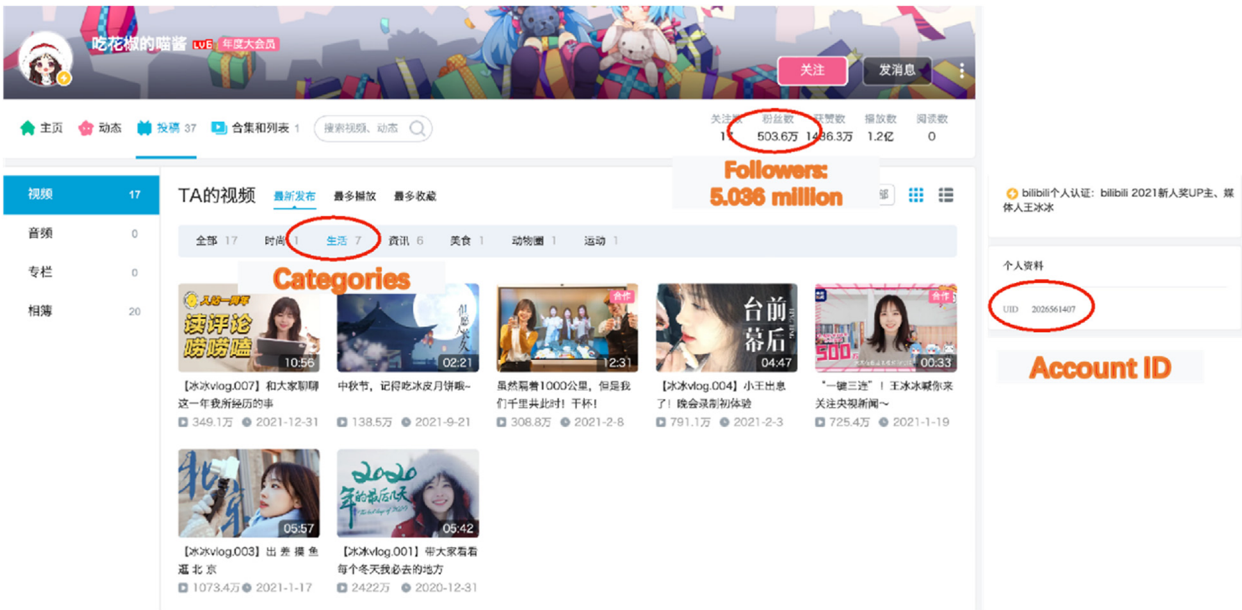

Fig. 5. Information data of "uploaders".

Fig. 6. Video feature data.

Fig. 7. Comments of a video.

5.1.2. Independent variables

The independent variables in this research are two dummy variables *Ad* and *InformedAd*, because we are primarily interested in the effect of sponsored content and its disclosure status on consumer engagement. If a video clip is tagged to be an advertisement, the value of *Ad* will be 1, otherwise it will be 0. If a video clip is tagged to be an advertisement with prior information disclosure, the value of *InformedAd* will be 1, otherwise it will be 0.

5.1.3. Control variables

The first type of control variables are video characteristics, including how many times a video has been watched (*views*), how long the video is (*length*) and how long it has been uploaded (*ReleasetoDate*). Logically, a video has to be viewed before it can receive any coins or other consumer engagement. The *length* of a video is also crucial because a video too short has limited content, while a video too long may scare away impatient consumers. Also, the longer a video has been uploaded, the more engagement it is likely to accumulate, so we also control for the time span since release.

The second type of control variables include the characteristics of video uploaders, such as number of *followers*、 account ID *uid* and whether the uploader belongs to *MCN* institutions. Intuitively, uploaders with a large number of followers or belong to MCN institutions are perceived to be more sophisticated, thereby being able to generate a higher level of consumer engagement. The variable *uid* is a unique ID number for an uploader which follows an ascending order corresponding to the time of registration. An uploader that registered 10 years ago will have a smaller *uid* number compared to one registered 10 days ago. Usually, "older" uploaders have a larger number of loyal fans, thereby potentially having a higher engagement level.

The third type of control variables are dummy variables of video content *genre*. For example, the variable *Annime* stands for a video posted on the Animation Section on the platform.

Table 1
Detailed meanings of the variables.

Variable	asdMeaning
lniews	Video view, i.e. number of times the video be played (logarithm form)
lnLikes	Number of users who like the video (logarithm form)
lnCoins	Number of coins the video received (logarithm form)
lnSave	Number of times the video be saved (logarithm form)
lnShares	Number of times the video be shared (logarithm form)
lnDanmaku	Number of bullet chats the video has (logarithm form)
lnComments	Number of comments the video has (logarithm form)
length	How long the video is
length_sq	Squared form of the video length
dayssincerelease	How long has the video existed on the platform
dsr_sq	Squared form of days since the video released
ad	If the video is categorized as “Sponsored Video”, it is 1; otherwise, it is 0
informed*ad	If the “Sponsored Video” has been informed in advance, it is 1; otherwise, it is 0
lnfollowers	Number of followers the “Uploader” has (logarithm form)
MCN	If the “Uploader” is signed by an MC, it is 1; otherwise, it is 0
Anime	If the video is released in Anime category, it is 1; otherwise, it is 0
Drama	If the video is released in Drama category, it is 1; otherwise, it is 0
Pets	If the video is released in Pets category, it is 1; otherwise, it is 0
Japanime	If the video is released in Japanime category, it is 1; otherwise, it is 0
Guichu	If the video is released in Guichu category, it is 1; otherwise, it is 0
Chinanime	If the video is released in Chinanime category, it is 1; otherwise, it is 0
Tech	If the video is released in Tech category, it is 1; otherwise, it is 0
Food	If the video is released in Food category, it is 1; otherwise, it is 0
Fashion	If the video is released in Fashion category, it is 1; otherwise, it is 0
Music	If the video is released in Music category, it is 1; otherwise, it is 0
Movie	If the video is released in Movie category, it is 1; otherwise, it is 0
Game	If the video is released in Game category, it is 1; otherwise, it is 0
Entertain	If the video is released in Entertain category, it is 1; otherwise, it is 0
Sports	If the video is released in Sports category, it is 1; otherwise, it is 0
Knowledge	If the video is released in Knowledge category, it is 1; otherwise, it is 0
News	If the video is released in News category, it is 1; otherwise, it is 0
Digital	If the video is released in Digital category, it is 1; otherwise, it is 0
Dance	If the video is released in Dance category, it is 1; otherwise, it is 0
lnmean_ad	IV variable of “ad”: the proportion of sponsored content in the other videos within the category to which the video belongs (logarithm form)
lnmean_infad	IV variable of “Informed*ad”: the proportion of informed sponsored content in the other videos within the category to which the video belongs (logarithm form)

5.2. Regression model

Based on previous analysis, we propose an OLS regression model to estimate the influence of sponsored content and its disclosure on consumer engagement. The key estimators we focus on are β_1 for variable *Ad* and β_2 for variable *InformedAd*. The benchmark regression model is as follows:

$$lnCoins = \beta_0 + \beta_1 Ad + \beta_2 InformedAd + \beta_3 lnViews + \beta_4 Length + \beta_5 Length^2 + \beta_6 ReleasetoDate + \beta_7 ReleasetoDate^2 + \beta_8 lnFollowers + \beta_8 UID + \beta_9 MCN + \sum_i \beta_i Genre_i$$

6. Empirical analyses

6.1. Benchmark regression

The benchmark regression results are presented in Table 3. Regressions (1) and (3) do not include the squared item of *length* and *ReleasetoDate* as control variables, while regressions (1) and (2) include variables that control for video *genres*.

The benchmark regression results are consistent with our previous hypotheses. We note that both β_1 and β_2 estimators are statistically significant at the 1% level. The results indicate that the number of coins received by sponsored content is approximately 20% lower than that of normal non-ad videos. This finding supports H1, which suggests that sponsored content has a lower level of consumer engagement due to negative externalities exerted by advertisements compared to normal user-generated video content.

Moreover, the results demonstrate that sponsored content with prior disclosure performed better than non-disclosed videos. This finding aligns with hypothesis H2, which posits that prior-disclosed sponsored content will have a higher level of consumer engagement compared to undisclosed sponsored content. Although this may seem counter-intuitive at first, the mechanism behind this result is not difficult to understand. As previously mentioned, a consumer's decision to watch a video depends on whether the expected return is higher than the opportunity cost of engaging in other forms of entertainment. If the realized return of watching a video turns out to be lower than their expected return due to unexpected sponsored content, it can negatively impact the consumer's welfare, thereby

Table 2
Summary statistics of data.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
lnviews	29918	11.77	1.99	3.61	17.58
lnLikes	29918	9.04	2.05	0.69	14.74
lnCoins	29918	7.15	2.44	0	14.91
lnSaves	29918	7.00	2.17	0	14.42
lnShares	29918	5.37	2.32	0	12.67
lnDanmaku	29918	5.95	2.28	0	13.06
lnComments	29918	5.76	1.68	0	11.84
length	29918	762.66	5775.69	3	426017
length_sq	29,918	3.39e+07	1.66e+09	9	1.81e+11
dayssincerelease	29,918	134.44	172.24	0	2394
dsr_sq	29,918	47739.77	165712.3	0	5731236
Ad	29918	0.05	0.22	0	1
Informed*ad	29918	0.02	0.15	0	1
lnFollowers	29918	3.97	1.45	0.07	7.44
MCN	29918	0.34	0.47	0	1
Anime	29918	0.07	0.25	0	1
Drama	29918	0.00	0.03	0	1
Pets	29918	0.01	0.07	0	1
Japanime	29918	0.00	0.03	0	1
Guichu	29918	0.03	0.16	0	1
Chinanime	29918	0.00	0.06	0	1
Tech	29918	0.04	0.20	0	1
Food	29918	0.03	0.17	0	1
Fashion	29918	0.10	0.30	0	1
Music	29918	0.06	0.23	0	1
Movie	29918	0.04	0.20	0	1
Game	29918	0.21	0.41	0	1
Entertain	29918	0.01	0.08	0	1
Sports	29918	0.00	0.06	0	1
Knowledge	29918	0.06	0.23	0	1
News	29918	0.01	0.08	0	1
Digital	29918	0.02	0.15	0	1
Dance	29918	0.02	0.14	0	1
lnmean_ad	20335	−3.04	0.37	−4.49	−1.82
lnmean_infad	20335	−3.77	0.36	−5.01	−2.61

reducing their intention to give coins to the video. On the other hand, informing consumers of the potential advertisement within a video can effectively reduce this negative externality and lead to increased consumer engagement.

6.2. Heterogeneity analysis

In this section, we further divide the sample into three groups based on the number of followers: macro-influencers with over 1 million followers, meso-influencers with followers between 100,000 and 1 million, and micro-influencers with fewer than 100,000 followers. We do this because in the real business world, brands often have budget constraints, and not all brands can afford to work with macro-influencers who charge higher prices for sponsored videos. Therefore, it is important to examine whether there are differences in the impact of sponsored content and its disclosure status across these different groups of influencers, as this information is crucial for advertisers when making decisions. In our heterogeneity analysis, we explore whether the effect of sponsored content and its disclosure status on consumer engagement varies among the different groups of influencers. The results of this analysis are presented in Table 4.

The regression results indicate that the effects of sponsored content and sponsorship disclosure are significant only for macro influencers, a phenomenon that is seldom discussed in existing literature and requires further analysis beyond the scope of this paper. Therefore, we will provide only some intuitive explanations for the discrepancy across uploader types.

In fact, we can assume that for any specific uploader, there is some heterogeneity among their followers. That is, there can be both *core* and *non-core* followers. Core followers, by definition, have a stronger emotional bond with the uploader, while non-core followers do not. It is reasonable to argue that the proportion of core followers of an uploader demonstrates some form of marginal diminishing properties. That is, the more followers an uploader has, the smaller the proportion of core followers should be. As the proportion of core followers decreases, the effect of sponsored content and its disclosure on consumer engagement will be determined primarily by the large proportion of non-core followers. Since non-core followers have a weaker bond with the uploader, they may be more sensitive to advertising content, thereby creating this tidal effect. Smaller uploaders, on the other hand, may have a higher proportion of core followers who are not so sensitive to advertisements. In fact, some core followers of small uploaders may even cheer and congratulate the uploader if they get the opportunity to make money from sponsored content through bullet chats, according to our observations. This argument is supported by the following results in Table 5, where meso-influencers and micro-influencers receive significantly more danmakus for their sponsored content.

Table 3
Benchmark regression.

	(1)	(2)	(3)	(4)
	lnCoins	lnCoins	lnCoins	lnCoins
Ad	−.183***	−.212***	−.183***	−.209***
	(.036)	(.036)	(.036)	(.036)
InformedAd	.27***	.285***	.281***	.292***
	(.055)	(.055)	(.056)	(.056)
lnViews	.945***	.941***	.938***	.934***
	(.006)	(.006)	(.006)	(.006)
releaseToDate	.001***	.002***	.001***	.002***
	(0)	(0)	(0)	(0)
RTDSquare		−.00***		−.00***
		(0)		(0)
length	−.00***	−.00***	−.00***	−.00***
	(0)	(0)	(0)	(0)
lengthSquare		−0***		−0***
		(0)		(0)
lnFollowers	.225***	.231***	.223***	.228***
	(.008)	(.008)	(.008)	(.008)
uid	−.00***	−.00***	−.00***	−.00***
	(0)	(0)	(0)	(0)
MCN	−.117***	−.116***	−.112***	−.114***
	(.015)	(.015)	(.014)	(.014)
Anime	.209***	.219***		
	(.028)	(.028)		
Drama	−2.73***	−2.669***		
	(.199)	(.197)		
Pets	−1.306***	−1.249***		
	(.085)	(.084)		
Japanime	−.937***	−.908***		
	(.166)	(.165)		
Guichu	.071*	.156***		
	(.038)	(.037)		
Chinanime	.621***	.588***		
	(.092)	(.09)		
Tech	−.219***	−.227***		
	(.032)	(.032)		
Food	−.042	−.007		
	(.044)	(.043)		
Fashion	.023	.007		
	(.022)	(.022)		
Music	.649***	.656***		
	(.026)	(.026)		
Movie	−.009	.007		
	(.035)	(.034)		
Game	−.052**	−.041**		
	(.02)	(.02)		
Entertain	.619***	.644***		
	(.088)	(.088)		
Sports	−.005	.052		
	(.077)	(.078)		
Knowledge	.329***	.327***		
	(.03)	(.03)		
News	−1.527***	−1.482***		
	(.125)	(.125)		
Digital	.107**	.126***		
	(.043)	(.042)		
Dance	.417***	.435***		
	(.034)	(.035)		
_cons	−4.897***	−4.975***	−4.765***	−4.846***
	(.049)	(.049)	(.047)	(.047)
Observations	29918	29918	29918	29918
R-squared	.784	.787	.772	.775

Robust standard errors are reported in the brackets, ***$p < .01$, **$p < .05$, *$p < .1$.

Table 4
Heterogeneity analysis.

	MacroInfluencer	MesoInfluencer	MicroInfluencer
	lnCoins	lnCoins	lnCoins
Ad	−.298***	.028	−.092
	(.039)	(.085)	(.564)
InformedAd	.391***	.055	−.086
	(.064)	(.108)	(.615)
lnViews	1.156***	.914***	.693***
	(.008)	(.007)	(.015)
releaseToDate	.001***	.002***	.003***
	(0)	(0)	(0)
RTDSquare	−0***	−0***	−0***
	(0)	(0)	(0)
length	0***	0***	0
	(0)	(0)	(0)
lengthSquare	−0***	−0***	−0*
	(0)	(0)	(0)
uid	−0***	−0***	−0***
	(0)	(0)	(0)
MCN	−.128***	−.093***	.123**
	(.02)	(.022)	(.057)
Anime	.355***	.142***	.091
	(.043)	(.038)	(.108)
Drama		−2.593***	
		(.193)	
Pets		−1.346***	
		(.083)	
Japanime			−1.297***
			(.158)
Guichu	.197***	.115**	.709***
	(.051)	(.055)	(.162)
Chinanime		.592***	
		(.092)	
Tech	−.133***	.06	1.274***
	(.038)	(.059)	(.127)
Food	−.114	−.021	−.206
	(.076)	(.05)	(.263)
Fashion	.161***	.069**	−.612***
	(.037)	(.028)	(.072)
Music	.74***	.723***	.417***
	(.038)	(.04)	(.089)
Movie	.108**	.107*	−1.411***
	(.042)	(.055)	(.099)
Game	.106***	−.253***	.126*
	(.027)	(.032)	(.075)
Entertain	.472***	.504***	1.358***
	(.09)	(.176)	(.145)
Sports		−.27*	−.273**
		(.143)	(.129)
Knowledge	.583***	.269***	−.265**
	(.043)	(.043)	(.114)
News	−1.542***	.918***	
	(.122)	(.12)	
Digital	.104*	.229***	.097
	(.055)	(.08)	(.103)
Dance	−.002	.45***	1.069***
	(.058)	(.045)	(.084)
_cons	−6.505***	−4.022***	−2.328***
	(.111)	(.078)	(.143)
Observations	12915	14543	2460
R-squared	.709	.62	.642

Robust standard errors are reported in the brackets, ***p < .01, **p < .05, *p < .1.

7. Robustness tests

7.1. Instrumental variables analysis

To address the issue of endogeneity, we employ instrumental variables analysis. There is a possibility that factors such as whether a video is sponsored content or not, and whether the advertisement is previously informed, may be influenced by the uploader's

Table 5
Heterogeneity analysis on danmakus.

	Head	Middle	Tail
	lnDanmaku	lnDanmaku	lnDanmaku
Ad	−.049	.335***	1.372***
	(.031)	(.083)	(.128)
InformedAd	.042	−.192*	−1.544***
	(.057)	(.102)	(.22)
lnViews	1.032***	.862***	.684***
	(.007)	(.007)	(.016)
releaseToDate	.001***	.001***	.002***
	(0)	(0)	(0)
RTDSquare	−0	−0***	−0
	(0)	(0)	(0)
length	0***	0***	0***
	(0)	(0)	(0)
lengthSquare	−0***	−0***	−0***
	(0)	(0)	(0)
uid	−0***	−0***	−0*
	(0)	(0)	(0)
MCN	−.013	−.026	.335***
	(.018)	(.022)	(.065)
Anime	−.333***	−.074**	−.068
	(.04)	(.037)	(.145)
Drama		−2.475***	
		(.2)	
Pets		−.967***	
		(.078)	
Japanime			−1.363***
			(.186)
Guichu	−.797***	−.636***	.859***
	(.044)	(.049)	(.135)
Chinanime		.481***	
		(.084)	
Tech	.046	.497***	1.646***
	(.037)	(.065)	(.172)
Food	−.006	−.107**	−.879***
	(.052)	(.051)	(.242)
Fashion	.103**	.242***	−.414***
	(.046)	(.033)	(.082)
Music	−.263***	−.383***	−.655***
	(.034)	(.037)	(.099)
Movie	.43***	.504***	−.981***
	(.033)	(.045)	(.104)
Game	−.138***	−.203***	.16*
	(.025)	(.031)	(.084)
Entertain	.64***	1.661***	1.016***
	(.103)	(.113)	(.123)
Sports		−1.239***	−1.846***
		(.104)	(.121)
Knowledge	.377***	.482***	−.407***
	(.041)	(.038)	(.145)
News	−.668***	1.378***	
	(.088)	(.105)	
Digital	.477***	.582***	.253
	(.035)	(.059)	(.172)
Dance	−.808***	−.339***	1.04***
	(.077)	(.055)	(.145)
_cons	−6.086***	−4.499***	−3.322***
	(.101)	(.079)	(.147)
Observations	12915	14543	2460
R-squared	.695	.605	.598

Robust standard errors are reported in the brackets, ***p < .01, **p < .05, *p < .1.

popularity, which in turn affects consumer engagement. Additionally, using cross-sectional data for regression may lead to the omission of relevant variables. To tackle this, we identify the category to which each video belongs and calculate the average level (proportion) of sponsored content, as well as the average level (proportion) of informed sponsored content, for videos other than the one under consideration within each category. These two average levels are then used as instrumental variables for "*Ad*" and "*Informed_Ad*" respectively. These instrumental variables satisfy the required correlation conditions. Each category on the user-generated content (UGC) platform represents a segmented market or industry. Due to social norms and market competition, uploaders are likely to be influenced by the behavior of their competitors in the same market. They may choose to imitate others or act differently in order to distinguish their videos from the rest. However, an uploader's video popularity is not directly affected by other uploaders' advertising behavior. As such, the main independent variables, "*Ad*" and "*Informed_Ad*," remain the sole influencing factors in our instrumental variables analysis. This approach helps mitigate the endogeneity issue and provides more robust results for our analysis.

The results of the instrumental variable regression analysis are presented in Table 6. To ensure the validity of our instrumental variables, we conducted under-identification and weak identification tests. The p-value of the Kleibergen-Paap rk LM statistic for the under-identification test is 0.005, indicating that our instrumental variables are valid. For the weak identification test, the Cragg-Donald Wald F statistic is 94.06, and additional weak-instrument-robust inference tests like the Anderson-Rubin Wald test and Stock-Wright LM S statistic further confirm the joint significance of the endogenous regressors.

The instrumental variable regression results are consistent with the benchmark results, and the absolute values of the coefficients are even larger, providing further confirmation of hypotheses H1 and H2. This strengthens our findings that sponsored content has a negative impact on consumer engagement compared to user-generated content (H1), and that sponsored content with prior-disclosure performs better than non-disclosed videos in terms of consumer engagement (H2). The instrumental variable analysis helps address the endogeneity issue and enhances the reliability of our results.

7.2. Substitute variables

In the robustness test section, we use other engagement metrics as dependent variables such as likes, comments, etc. The results are shown in Table 7.

Overall, the regression results are consistent with the benchmark regression, where sponsored content generates a negative response from consumers, and prior disclosure of sponsorship offsets the negative impact of advertisements. However, we do notice that regression (4) shows inconsistent results compared to other findings. In this particular regression, there is no significant correlation between the number of danmaku and sponsored content, as well as prior disclosure of sponsorship. This can be explained by certain consumer behavior habits on Bilibili, which we mentioned in the data and methods section. As previously stated, we tagged sponsored content based on the content of comments and danmakus. On the Bilibili platform, consumers have a tradition of posting danmakus expressing their surprise or unexpected discovery when they encounter a video containing sponsored content. These additional danmakus contribute to an increase in the number of danmakus for sponsored content compared to non-ad videos. As a result, the number of danmakus may not accurately reflect consumer engagement with sponsored content, leading to the inconsistent results observed in regression (4). Despite this minor inconsistency, the overall pattern of results remains consistent, and the main findings regarding the

Table 6
Instrumental variable estimation.

	Benchmark	IV
	lnCoins	lnCoins
Ad	−.212***	−.887***
	(.036)	(.160)
InformedAd	.285***	1.445***
	(.055)	(.318)
Controls	YES	YES
_cons	−4.975***	−4.539***
	(.049)	(0.062)
Observations	29918	20335
R-squared	.787	.796

Robust standard errors are reported in the brackets, ***p < .01, **p < .05, *p < .1.

Table 7
Substitute variables.

	(1)	(2)	(3)	(4)	(5)	(6)
	lnCoins	lnLikes	lnSaves	lnDanmaku	lnShares	lnComments
Ad	−.212***	−.063***	−.266***	.038	−.347***	−.136***
	(.036)	(.016)	(.03)	(.03)	(.037)	(.022)
Informed_ad	.285***	.044*	.168***	−.001	.283***	.261***
	(.055)	(.024)	(.046)	(.048)	(.055)	(.034)
Controls	YES	YES	YES	YES	YES	YES
_cons	−4.975***	−2.137***	−4.74***	−5.218***	−6.515***	−2.881***
	(.049)	(.022)	(.04)	(.049)	(.043)	(.032)
Observations	29918	29918	29918	29918	29918	29918
R-squared	.787	.94	.814	.772	.783	.813

Robust standard errors are reported in the brackets, ***p < .01, **p < .05, *p < .1.

negative impact of sponsored content and the positive effect of prior disclosure on consumer engagement are robust across various regression models.

8. Conclusions and discussions

As the Internet continues to play an increasingly significant role in our daily lives, we are witnessing a growing trend of young individuals, including college students, becoming content creators on video platforms like Bilibili. The rapid advancements in technology have made content creation a feasible career path for almost anyone with a mobile phone. Monetization opportunities in this profession mainly revolve around advertising revenues, particularly through sponsored content. In this study, we focused on two types of sponsored content: one with prior disclosure of sponsorship and one without. Our aim was to examine the differences in consumer engagement between these two forms of sponsored content. We found that, on the whole, sponsored content tended to decrease the level of consumer engagement. However, we also observed that prior disclosure of sponsorship had a significant positive effect in offsetting the negative impact on consumer engagement. Moreover, we conducted an analysis to compare the effects across different types of uploaders or influencers. Surprisingly, the results indicated some disparities in the impact of sponsored content and its disclosure status among macro, meso, and micro-influencers. We provided some plausible explanations for these differences.

This study carries two important practical implications. Firstly, it offers valuable guidance to content uploaders on whether they should disclose sponsorship information in their videos. Understanding the impact of sponsorship disclosure can help content creators make informed decisions to optimize consumer engagement and satisfaction. Secondly, our research results indicate that regulatory agencies and video platforms should collaborate to promote the practice of prior disclosure of sponsorship information. In the US, such regulations have already been implemented, and our study supports the implementation of similar regulations in China to enhance consumer protection. By encouraging transparency and disclosure, consumers can make more informed choices, and the overall user experience on UGC platforms can be improved.

However, there are still some topics that require further exploration. Firstly, advanced computer technologies can be utilized to identify and categorize data more effectively. Due to our limited resources, we only utilized the text information of videos, leaving the audio and visual information untouched. Secondly, a more comprehensive theory could be proposed for the heterogeneity analysis of this study to better explain the variations across macro to micro influencers.

Declaration of competing interest

Di Zhou is an editorial board member for Journal of Digital Economy and was not involved in the editorial review or the decision to publish this article. All authors declare that there are no competing interests.

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