**The Impact of AI-Generated Summaries on Video Consumption:**
**Insights from A Randomized Field Experiment**


## Abstract

Generative artificial intelligence (AI) has been increasingly adopted for content generation on online platforms. One prominent application of this technology is to craft concise and synthetic summaries of video content, which is of greater lengths and complexity originally. However, the impact of such AI-generated summaries (AIGS) on consumption with original content has rarely been examined. In this study, we conduct a randomized field experiment on a major online video-sharing platform in China. We augment AIGS to the review section of videos in the treatment group and meticulously monitor multiple consumer behaviors, including views, likes, shares, reviews, and virtual tips. Our findings reveal that the inclusion of AIGS notably enhances all consumption activities. Further investigations show that when AIGS coexist with user-generated reviews, their influences tend to diminish in information-rich environments characterized by a higher volume of reviews, neutral discussions, and divergent opinions among peer consumers. Moreover, the effects of AIGS are heterogeneous with video features, such as content type, length, and age. Our exploratory analysis on AIGS content suggests that when AIGS are perceived as more credible through content consistency and social cues, consumers are more likely to engage in video consumption. These results highlight the informative and persuasive roles AIGS plausibly play in driving engagement. Our research sheds light on the substantive effects of AIGS on online platforms and enriches the burgeoning literature on the utilization of generative AI in content consumption. The research insights have profound implications for marketers, content creators, and platforms.



Keywords: AI-generated summaries (AIGS), video consumption, field experiment, information, persuasion

**The Impact of AI-Generated Summaries on Video Consumption: Insights from A Randomized Field Experiment**

## 1. Introduction

Generative artificial intelligence (AI) has garnered significant interest, enticing researchers and practitioners to delve into its applications and implications. This advanced technology has been found powerful in accomplishing text-to-text and text-to-image tasks, thereby improving the efficiency of content production (Noy and Zhang 2023; Zhou and Lee 2024). It can also generate responses about perceptions and preferences of products in the market that mimic those from actual consumers (Goli and Signh 2024; Li et al. 2024). Moreover, generative AI can perform transformation between videos and other modalities (e.g., Sora from OpenAI turns text into videos). An emerging genre of AI-generated content (AIGC in short)—AI-generated summaries (AIGS hereafter)—converting different formats of content into textual summaries using generative AI, is gaining popularity in mainstream online platforms. For instance, Amazon embeds AIGS to summarize consumer reviews[1] and displays the AIGS of reviews above authentic consumer reviews (Su et al. 2024). It is now also feasible to distill lengthy and intricate video content into succinct textual summaries with generative AI, which could then be consumed by viewers prior to their consumption of the original videos from online video platforms such as YouTube, Vimeo, TikTok, Bilibili, among others. For instance, an AI YouTube Summary tool powered by ChatGPT can efficiently generate concise and accurate summaries integrated with the platform.[2] Similarly, NoteGPT claims to provide unlimited video summarization for videos both on Vimeo and YouTube.[3] By reading this condensed information, individuals can grasp the essence of the content without dedicating substantial time to content consumption.

[1] See https://www.aboutamazon.com/news/amazon-ai/amazon-improves-customer-reviews-with-generative-ai, accessed on 8 October 2024.
[2] See https://monica.im/en/features/youtube-summary-with-chatgpt, accessed on 8 October 2024.
[3] See https://notegpt.io/blog/video-summarization-for-vimeo, and https://notegpt.io/youtube-video-summarizer, accessed on 8 October 2024.

Recent studies have started to explore the effectiveness of content summaries on various online platforms. Su et al. (2024) investigated the use of AIGS in e-commerce, where the platform employs a generative AI tool to create condensed summaries of existing consumer reviews. Their research indicates that the implementation of AIGS results in an increase in both the volume and richness of reviews. Focusing on video content, Yang et al. (2024) examined the effect of user-generated, rather than AI-generated, condensed clips derived from full-length videos on the demand for original works. Similarly, they found positive spillover effects, implying that these condensed clips help to enhance the visibility of original works and subsequently boost their demand. However, the user-generated condensed clips studied in Yang et al. (2024) typically highlight specific segments of original videos and are distributed through different channels, rather than the platform where the original works are posted, to engage consumers. In contrast, AIGS of videos offer comprehensive synopses of the entire content and are usually displayed alongside the original videos within the same channel. In our study, we focus on AIGS derived from video content, which are presented on the same channel as the original videos. Despite the growing prevalence of AIGS, it remains unanswered whether this new form of summaries can impact the consumption with video content, and if so, how. On one hand, AIGS can expedite consumers' navigation through the original content, thereby enhancing their understanding of the content and allowing them to focus on the most valuable parts (Leavitt and Christenfeld 2013). On the other hand, AIGS are naturally spoilers, which can potentially detract viewers from the enjoyment and sense of surprise in content consumption, thereby reducing their desire to consume the content (Ryoo et al. 2021). Existing research has yet to systematically address this tension, leaving a gap in understanding how AIGS balance the benefits of information accessibility with the potential drawbacks of spoiling content.

More interestingly, the AIGS of video content is displayed in the review section alongside user-generated content (UGC) in our research context (see Figure 1 for an illustration). It is worth noting that this AIGS differs significantly from traditional user-generated reviews that are rooted in consumers' personal experiences and evaluations (Zhao et al. 2012; Chae et al. 2017). Online user-generated reviews have been proven to help consumers learn the quality of videos (Chen and Xie 2005; Chevalier and Mayzlin

2006; Gu et al. 2012) and influence consumption decisions (Duan et al. 2008; Shin et al. 2022; Zhu and Zhang 2010). In contrast, AIGS are created by AI technology to provide objective overviews, encapsulating detailed information about the original content without being influenced by individual biases or subjective consumption experiences. The presence of AIGS introduces a new layer of information that could either complement or substitute with user-generated reviews in shaping consumer perceptions. While user-generated reviews often capture the subjective emotional reactions and nuanced perspectives of individual consumers, and may sometimes include selective information related to products or services, AIGS offer a structured, data-driven summary of the entire video, potentially catering to consumers seeking a quick and comprehensive understanding. However, the influence of AIGS on video consumption, particularly when presented alongside user-generated reviews, remains unclear. Our study seeks to address this gap by exploring how these distinct sources of information interact and influence consumer behavior.

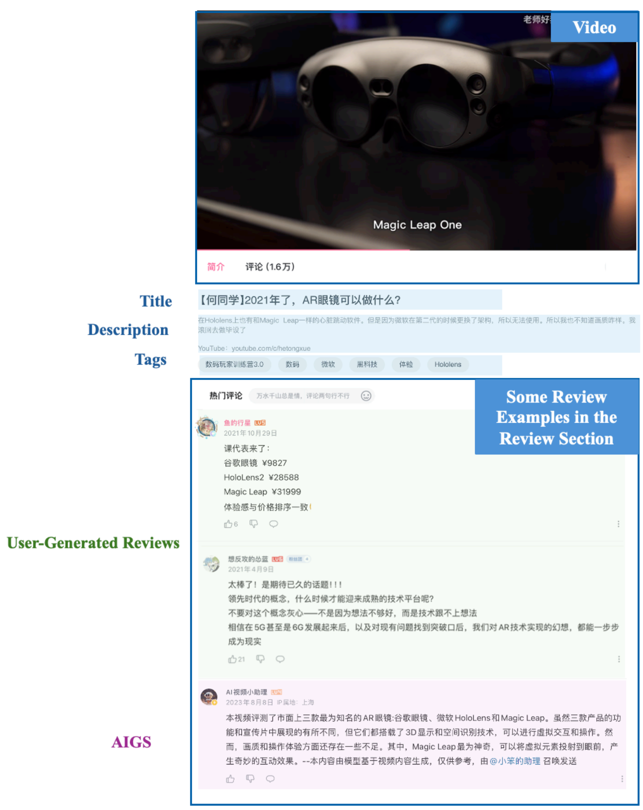


**Figure 1: An Example of Video, AIGS and User-Generated Reviews in Chinese**

Our research sets out to investigate the effects of AIGS in online video consumption, and the heterogenous effects of AIGS in the presence of user-generated reviews and across various video features.

Following extant literature (e.g., Lee et al. 2018; Susarla et al. 2011), we examine their effects on various consumption behaviors, including views, likes, shares, reviews, and virtual tips for the original content. It is imperative to recognize that these consumption activities differ from each other in terms of the levels of effort and deliberate thinking that are needed (Yang et al. 2019; Rajaram and Manchanda 2024). Specifically, viewing and liking are usually fast and intuitive, requiring less effort, whereas sharing,[4] writing reviews, and donating virtual tips necessitate more deliberation time, cognitive resources, and costs. The comprehensive analysis of various consumption activities offers not only valuable insights into nuanced consumer behavior but also the economic implications of AIGS to different stakeholders. For instance, platforms like TikTok places significant emphasis on play duration, likes, shares, and reviews when evaluating the performance of new creators.[5] In addition, advertisers often rely on video performance metrics when choosing an influencer for sponsorship (Yang et al. 2023).

To investigate the effects of AIGS, we conducted a randomized field experiment on one of the largest Chinese online video-sharing platforms. In the experiment, AIGS of videos were created and inserted in the review section in the treatment group, providing consumers with a concise, objective overview of the video content. In contrast, no such AIGS were administrated for a set of comparable videos in the control group. Daily metrics of various consumption activities, including views, likes, shares, reviews, and virtual tips, were tracked for the videos in both the treatment and control groups from the time of their release. By applying a difference-in-differences (DID) model, we find that the inclusion of AIGS significantly boosts video consumption. Videos in the treatment group experienced notable increases in various consumption activities, ranging from 2.46% and 14.2%, compared to those in the control group. Our further exploration of underlying mechanisms reveals that when AIGS and user-generated reviews work together, the informative influence of AIGS tends to diminish when user-generated reviews have

[4] When sharing a video, consumers do more than simply click a share button; they must also deliberate on the appropriate platform, the target audience, and whether to provide personal commentary accompanying the shared content.
[5] See https://newsroom.tiktok.com/en-us/introducing-the-new-creator-rewards-program, accessed on 8 October 2024.

provided rich information and insights, such as in cases of a higher volume of reviews, neutral discussions, or divergent opinions among consumers. In addition, the influences of AIGS also vary with video features in a way that aligns with the informative role played by AIGS. Specifically, the effects of AIGS on post-viewing behaviors are more pronounced if the video content requires higher cognitive efforts to process, which include when the videos are utilitarian in nature, or they are longer in duration. We also find that the effects of AIGS are more pronounced when videos are at their early stages, therefore presumably only limited information regarding video performance metrics and user-generated reviews have been posted. Besides the informative role, we also obtain some evidence on the persuasive role of the AIGC, via content analysis. Based on the exploratory analysis of the subsample from those treated videos, we examine the correlation between AIGS content and video consumption. The results suggest that when content of AIGS is more credible—either it is more consistent with existing informational cues such as the title, description, and tags of the video, or social cues such as likes received by the AIGS—consumers are more likely to be persuaded to engage in the consumption of the original video. Interestingly, our exploratory analysis leads to a non-linear effect of AIGS ranking, which contrasts with prior findings that more prominent positions generally increase the influence of online user-generated reviews (e.g., Liu et al. 2019; Wu et al. 2015).

Our research makes several significant contributions. First, while the extant literature has examined the effects of generative AI on text-to-text and text-to-image transformations (e.g., Chen and Chan 2023; Noy and Zhang 2023; Su et al. 2024; Zhou and Lee 2024), our research focuses on the video-to-text application on online platforms. We quantify the influence of AIGS on online video consumption through a randomized field experiment. Previous studies have predominantly focused on the impact of specific video features, such as audio, visuals, and duration, on viewers' consumption behaviors (e.g., Gu and Zhao 2024; Rajaram and Manchanda 2024). Our analysis, however, extends beyond video features and assesses the effects of AIGS as interventions that encapsulate the entire video content on various consumption behaviors, thereby augmenting the body of literature on video consumption. Second, our research investigates the interplay between AIGS and user-generated reviews, which are displayed together in our research context. Created by generative AI and offering comprehensive summaries of the entire content objectively, AIGS are distinct from traditional user-generated reviews in both information source and content nature, but they synergistically interact with each other to affect consumer decisions. Benefiting from our unique experimental setup, we uncover a nuanced and intriguing interaction between these two types of information. Our findings extend UGC literature by enriching our understanding of how user-generated reviews and AIGS work together to influence different consumption behaviors. Third, we further explore the underlying mechanisms of AIGS, focusing on their informative and persuasive capabilities through a series of analyses. The results show that the effectiveness of AIGS on video consumption varies with various video features, including video type, length, and age. Moreover, we delve into the AIGS content and demonstrate a strong association between the perceived credibility of AIGS and video consumption. This paper provides important practical implications for content creators, marketers, and platforms. Our research findings offer valuable guidance for leveraging AIGS as an effective tool to enhance video consumption.

The rest of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 introduces the experimental design. Section 4 presents the main results regarding the impact of AIGS on video consumption. Section 5 delves into the underlying mechanisms. Section 6 concludes this study.

## 2. Related Literature

Our study aims to investigate the effects of AIGS on video consumption through a randomized field experiment. In this section, we review the recent studies on generative AI. We also undertake a review of studies related to the context of online video consumption and online user-generated reviews. We explain how our study builds on and contributes to these three streams of literature.

### 2.1 Generative AI

The advent of generative AI, with its remarkable ability to produce high-quality and human-like content across various formats, has sparked significant interest in both its promise and peril (Epstein et al. 2023; Stokel-Walker and Van Noorden 2023). This technology enables the efficient and cost-effective creation of content, which traditionally requires substantial human effort (Cao et al. 2023; De Freitas et al. 2023;

Kumar and Kapoor 2023). By harnessing AI's automated production capabilities, individuals can significantly enhance content productivity (Noy and Zhang 2023). However, this advancement also poses challenges to content novelty and the labor market (Hui et al. 2024; Zhou and Lee 2024). AIGC encompasses multiple digital forms, including text, images, and videos (Cao et al. 2023), and has demonstrated considerable efficiency in various business applications, such as search engine optimization, creative advertising, and customer service chatbots. These applications have led to significant improvements in production efficiency, business performance, and customer engagement (Burtch et al. 2024; Chen and Chan 2023; De Freitas et al. 2023; Reisenbichler et al. 2022).

AIGS represents a novel genre of AIGC that has gained popularity on online platforms. Unlike the AIGC explored in previous literature (Cao et al. 2023), which typically transforms text into other content modalities (e.g., images, music, or videos), AIGS perform a reverse transformation by summarizing existing content into concise text. Online platforms like Amazon and Yelp have implemented AIGS to synthesize key consumer opinions from reviews for facilitating consumer decision-making (Schermerhorn 2023). Su et al. (2024) examined the role of AIGS in condensing consumer reviews on Amazon and found it effective in increasing both the volume and richness of subsequent reviews. Beyond its application in consumer reviews, AIGS have also become prevalent on online video-sharing platforms such as YouTube, Vimeo, TikTok and Bilibili, where it transforms video content—considered a more complex medium than text reviews—into comprehensive textual overviews. Previous research has highlighted the positive impact of content disclosure on consumption behaviors. For instance, Ryoo et al. (2021) found that movie spoilers, which reveal key plot details, have positive relationship with box office revenue. Similarly, Yang et al. (2024) demonstrated a positive impact of user-generated video clips on the demand of original content. Despite these findings, to our best knowledge, there has been little systematic research investigating the influence of AIGS on video content consumption. Our study attempts to address this gap, contributing to a deeper understanding of the role of generative AI on online platforms (Wessel et al. 2023).

### 2.2 Online Video Consumption

Online video consumption is an important economic driver and represents one of the fastest-growing consumer service offerings (Zhou et al., 2021). Previous research has examined various video features that influence consumption. For instance, Rajaram and Manchanda (2024) found that factors like music duration and the size of human images are positively associated with video engagement. Yang et al. (2023) focused on product placement in the video. Nevertheless, the fundamental factor influencing consumption behaviors is the video content itself. Well-designed content has been shown to enhance consumer engagement and focus (Zhang et al. 2020). Before fully committing to a video, consumers often rely on introduction content, including titles, descriptions, and tags to inform their decisions. However, video introduction content is constrained by length, limiting the amount of information they can convey. Additionally, as content creators strive to craft eye-catching titles and descriptions to attract consumers (Tafesse 2020), issues of information asymmetry arise (Chen and Xie 2005; Liu et al. 2017). To resolve this information asymmetry, a straightforward approach is to watch the video, neglecting the potentially significant investment in time and effort. Some videos may last for over a few minutes or even several hours, making time and effort investment a serious concern in consumption decisions. Gu and Zhao (2024) suggest that platforms can enhance consumer engagement and improve market performance by optimizing content length. To address the constraint of limited time and information, content summaries have emerged as an effective tool, enabling consumers to quickly grasp the essence of videos and reduce uncertainty. User-generated condensed clips, which summarize films and television series, have gained popularity on video-sharing platforms and have been shown to increase consumers' demand by enhancing the visibility of original content (Yang et al. 2024). However, while these clips cater to consumers' desire for a quick understanding of the original videos, they often only focus selectively on appealing segments of the original content, and are distributed through separate channels. As a result, the information available on the original channel remains limited, offering a partial view rather than a comprehensive summary of the entire video.

In contrast, advanced generative AI technology enables the rapid and automatic production of comprehensive video summaries, making AIGS widely applicable. As a novel application of generative AI, AIGS allow consumers to efficiently understand the essence of a video without watching it in full. These informative summaries may therefore facilitate consumers to further engage with the video. On the other side, more information does not necessarily enhance the consumption experience, as excessive spoilers may detract from the enjoyment and sense of surprise (Ryoo et al. 2021). Over-disclosure could diminish the gratification consumers can derive from the content, thereby negatively affecting their overall consumption (Johnson and Rosenbaum 2015). To address this tension, our study examines how the disclosure of video content through AIGS affects various consumption behaviors, including views, likes, shares, reviews, and virtual tips on an online video-sharing platform. Since these behaviors differ in the level of consumers' effort and deliberation required (Yang et al. 2019; Rajaram and Manchanda 2024), analyzing them provides nuanced insights into the impact of AIGS on video consumption.

### 2.3 Online User-Generated Reviews

AIGS are presented in the review section and coexist with user-generated reviews in our research context. Traditional online reviews are typically written by humans (Fang 2022; Deng et al. 2021; Kim et al. 2019). In contrast, AIGS represent a novel type of content—written by generative AI without authentic consumption experience. User-generated reviews are usually generated and shared after consumers engage in personal consumption experiences of the products or services, either fully or partially (Chae et al. 2017; Lee et al., 2021; Zhao et al. 2012). These reviews often reflect individual preferences toward different attributes and are subject to reporting bias, as consumers with extreme experiences are more likely to post reviews (Berger 2014; Chen and Xie 2005; Karamana 2021; Kwark et al. 2014). In some cases, users may inlucde product- or content-related information in their reviews. Nevertheless, the information disclosed by users is often incomplete and tends to highlight selective points that support personal evaluations. In comparison, AIGS provide a more objective and comprehensive overview of the video, which is free from subjective evaluation and potentially takes a more balanced and neutral standpoint.

Many previous studies have examined the impact of user-generated reviews. One primary function of online user-generated reviews is providing information. Consumers rely on these reviews to assess product quality (Chen and Xie 2008; Chevalier and Mayzlin 2006; Gu et al. 2012), which in turn affects consumers' attitudes towards the product and their consumption decisions (Li and Zhan 2011; Lu et al.

2013; Reich and Maglio 2020). Beyond the information from peer consumers, the emergence of AIGS serves as another information source that influences consumer behaviors. Given the differences between these two types of information sources and content nature, a critical question arises: will the information from humans (i.e., user-generated reviews) complement or substitute the effect from AI (i.e., AIGS)? Understanding this interaction is crucial for understanding how consumers process and respond to different information in the review section. Our study further expands the UGC literature by introducing AIGS as a new form of content and examining its interaction with traditional user-generated reviews, shedding light on how these distinct sources of information work together to influence consumer behavior.

## 3. Field Experiment

### 3.1 Research Context and the AIGS Tool

We examined the effect of AIGS through a randomized field experiment on one of the largest online video-sharing platforms in China. The platform embeds an "AI Assistant" tool, which is accessible to consumers of the platform to generate a condensed summary in the form of text for the video of interest.[6] Since its launch in June 2023, the tool has rapidly gained popularity, attracting nearly 500,000 followers and being widely adopted by platform consumers. The process of using the "AI Assistant" tool comprises four steps: (1) the tool receives a consumer's request with an input of video link and a prompt to generate textual summary of the video; (2) the tool processes the video using speech recognition algorithms to transcribe spoken words into text format; (3) Natural Language Processing (NLP) techniques are applied to analyze the entire text content, extract key topics and main content, and generate a concise summary of

[6] Please noted that the platform introduced another beta version of AIGS function recently, which provides a button below the video content, allowing consumers to click if they wish to read the AIGS of the video. Once clicked, the AIGS is displayed in a sidebar adjacent to the video. However, this functionality is currently limited to the web version of the platform, which is used by only 10% of the platform's active user base, with the remaining 90% accessing content via mobile devices. In contrast, our "AI Assistant" tool was enabled by the platform before the launch of this function. The "AI Assistant" tool differs from the AIGS button in several aspects: (1) it is requested by a consumer by calling the tool to create the AIGS; (2) once created, the AIGS is inserted into the review section, making it accessible to all consumers, regardless of whether they are using the web or mobile application. Therefore, rather than relying on web consumers' decision of clicking the AIGS button, our experiment design alleviated the endogenous concern of selection bias regarding consumers' click decision and device access. We randomly insert the AIGS into a group of videos while leaving another comparable group without AIGS intervention in our experiment.

the video; (4) the tool delivers the summary to consumers by displaying the output in the review section of each video, following existing user-generated reviews. Given that the tool relies on audio information to retrieve content, it is not applicable to videos that lack speech content and rely solely on visual images. Additionally, the tool cannot generate summaries for videos shorter than one minute.

### 3.2 Experiment Design

Utilizing this "AI Assistant" tool, we conducted a randomized field experiment from November 2023 to February 2024. Particularly, our experiment design follows three steps: In the first week, we collected the videos newly posted on the platform to create a video pool; In the second week, we randomly selected a sample of videos from the video pool to be treated (i.e., creating an AIGS for them and supplementing the AIGS to their review section) and another sample of videos as the control group. In the last week, we recorded the status of the videos without any further intervention. The following reports the details of each step.

*Video Collection*: Each day during the first week, we collected a video pool from all newly posted videos, covering four categories: *game, food, knowledge, and technology*. This process was enabled by a specific section on the platform that displayed all videos in these categories.[7] Upon collection, we recorded each video's key characteristics including the post date, length, title, description, and tags, as well as the creator's information such as the number of followers. Additionally, we tracked the performance metrics of each video on a daily basis before manipulation, including views, likes, shares, reviews, and virtual tips (in coins).[8]

*Manipulation*: Each day during the second week, we randomly selected 40 videos (10 from each category) to the treatment group and another set of 40 videos (10 from each category) to the control group from the video pool. We ensured that no AIGS had been created to the videos selected in either treatment or control groups. To add an AIGS to the videos in the treatment group, we used the experiment account (a

[7] The Platform designates videos uploaded within the past three days as newly posted, and we exclude any videos that have been previously collected to maintain the integrity of the video pool.
[8] Coins are a form of virtual tips on the Platform, specifically used to reward videos. Consumers can primarily acquire coins through daily log-ins and by receiving rewards from peers for their own videos.

user account of the platform) to call the "AI Assistant" tool. The generated summaries were inserted into the review section of each treated video. Considering that only a very small number of videos were treated every day, as compared to the sheer volume of the new videos added to the platform, the treated videos were unlikely to have a spillover effect on untreated videos. For the videos in the control group, the manipulation date was set as the day that they were randomly picked even though no condensed summaries were sent to their reviews. The manipulation was conducted on a rolling basis. That means, if videos were not sampled in the current manipulation, they would remain in the video pool and could be selected in future manipulation.

*Observation*: We refrained from any further intervention during the last week and continued recording the performance metrics of all the videos, all of which were cumulative and readily available from the platform. With these cumulative metrics, we calculated the daily performance metrics of each video, including daily views, likes, shares, reviews, and virtual tips, which are the main dependent variables for subsequent analysis.[9] We kept the observation window within one week to minimize the potential disturbance from other events.

We repeated the above procedure for *four rounds* and each round of the experiment comprised three weeks. The interval between the manipulation of each round was two weeks. Figure 2 provides a visual depiction of the experiment. We designed our experiment in this way for two primary reasons: First, the age of a video (measured as the number of days since posting) posted during the first round would reach 79 days by the final round of manipulation, and the videos remaining in the pool were rolled over to later rounds of the experiment and could be sampled in our final data. The diverse range of age ensures that our random samples represent various stages of the video life cycle. Figure 3 depicts the timeline of our four-round experiment, illustrating the evolving video age range and the cumulative number of videos in the treated and control groups throughout the experiment. Second, pooling data from multiple rounds of manipulation increases the statistical power of the analysis and facilitates the identification of the effects.

[9] When calculating daily reviews, the AIGS reviews inserted for treated videos are excluded from the total review count.

In addition to the main analyses on pooled sample, we also analyze the data from each round of manipulation to check the robustness of the effects. The results of each round are qualitatively the same as the main results and are presented in Appendix A.

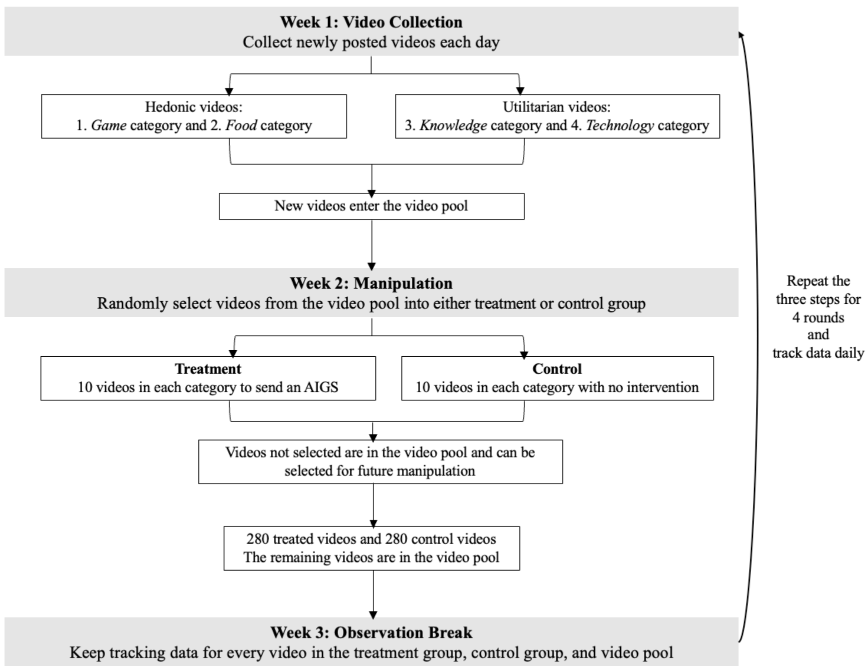


**Figure 2: Experimental Design**

**Round 1**

| | Week 1: Video Collection | Week 2: Manipulation | Week 3: Observation Break |
|---|---|---|---|
| *Min of Video Age* | 0 | 1 | 8 |
| *Max of Video Age* | 9 | 16 | 23 |
| *No. of Treated Videos* | 0 | 280 | 280 |
| *No. of Control Videos* | 0 | 280 | 280 |

**Round 2**

| | Week 1: Video Collection | Week 2: Manipulation | Week 3: Observation Break |
|---|---|---|---|
| *Min of Video Age* | 0 | 1 | 8 |
| *Max of Video Age* | 30 | 37 | 44 |
| *No. of Treated Videos* | 280 | 560 | 560 |
| *No. of Control Videos* | 280 | 560 | 560 |

**Round 3**

| | Week 1: Video Collection | Week 2: Manipulation | Week 3: Observation Break |
|---|---|---|---|
| *Min of Video Age* | 0 | 1 | 8 |
| *Max of Video Age* | 51 | 58 | 65 |
| *No. of Treated Videos* | 560 | 840 | 840 |
| *No. of Control Videos* | 560 | 840 | 840 |

**Round 4**

| | Week 1: Video Collection | Week 2: Manipulation | Week 3: Observation Break |
|---|---|---|---|
| *Min of Video Age* | 0 | 1 | 8 |
| *Max of Video Age* | 72 | 79 | 86 |
| *No. of Treated Videos* | 840 | 1120 | 1120 |
| *No. of Control Videos* | 840 | 1120 | 1120 |

**Figure 3: Experimental Timeline**

### 3.3 Data

Throughout the experiment, we randomly assigned 1,120 videos ($40\ videos \times 7\ days \times 4\ rounds$) to the treatment group and another 1,120 videos to the control group. We dropped videos that no longer existed by the end of the experiment and those in the control group where an AIGS was inserted by other consumers after manipulation, which led to an attrition of 82 videos. We also carefully checked if the AIGS were successfully added to the reviews of the videos in the treatment group, and found they were missing for 81 videos, likely being blocked by the platform. For 17 videos, the AIGS were displayed initially but were deleted by their creators afterwards. We also dropped these videos. In the remaining treated videos, we ensured that there was only one AIGS inserted during our experiment window. The ultimate sample includes 981 videos in the treatment group and 1,079 videos in the control group. Table 1 reports the definition and summary statistics of the dependent variables of our analysis, as well as other variables related to existing user-generated reviews, video features, and creators.

**Table 1: Definitions of Variables and Summary Statistics**

| | Description | Mean | Standard deviation | Min. | Max. |
|---|---|---|---|---|---|
| **Dependent Variables** | | | | | |
| $DailyViews_{it}$ | Daily number of views of video $i$ on day $t$ | 821 | 6910 | 0 | 727,072 |
| $DailyLikes_{it}$ | Daily number of likes of video $i$ on day $t$ | 27.8 | 392 | 0 | 47,352 |
| $DailyShares_{it}$ | Daily number of shares of video $i$ on day $t$ | 1.45 | 17.2 | 0 | 1,851 |
| $DailyReviews_{it}$ | Daily number of reviews of video $i$ on day $t$ | 1.37 | 9.51 | 0 | 726 |
| $DailyTips_{it}$ | Daily number of virtual tips of video $i$ on day $t$ in coins | 3.75 | 71.1 | 0 | 7,075 |
| **Existing User-Generated Reviews** | | | | | |
| $Volume_i$ | Number of user-generated reviews of video $i$ before manipulation | 151.3 | 417.3 | 0 | 8,027 |
| $Positivity_i$ | Average positivity of user-generated reviews of video $i$ before manipulation | .0303 | .0724 | -.5 | 1 |
| $Neutrality_i$ | Average neutral rate of user-generated reviews of video $i$ before manipulation | .806 | .301 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| $Divergence_i$ | Standard deviation of positivity of user-generated reviews of video *i* before manipulation | .101 | .0864 | 0 | .707 |
| **Videos** | | | | | |
| $Type_i$ | Type of video *i*<br>1 = utilitarian, 0 = hedonic | 0.492 | 0.500 | 0 | 1 |
| $Length_i$ | Length of video *i* in minute | 8.39 | 18.0 | 1 | 248 |
| $ManipulationAge_i$ | Number of days that video *i* has been posted until manipulation day (manipulation date - post date) | 23.6 | 19.5 | 1 | 78 |
| $Age_{it}$ | Number of days that video *i* has been posted until day *t* (data date - post date) | 23.9 | 19.7 | 0 | 85 |
| $Tag_i$ | Number of tags of video *i* | 9.14 | 3.05 | 3 | 14 |
| **Creators** | | | | | |
| $Followers_{it}$ | Number of creator's followers of video *i* on day *t* | 87,555.6 | 299,370.9 | 0 | 4,636,541 |

### 3.4 Randomization Checks

We conduct randomization checks to compare the videos assigned to the treatment group with those assigned to the control group in the final sample on key performance metrics (views, likes, shares, reviews, and virtual tips), as well as features related to existing user-generated reviews, videos, and creators before the manipulation. The results shown in Table 2 confirm that there are no significant differences between the two groups of videos prior to the manipulation.

**Table 2: Randomization Check**

| | Mean Control Group (N = 1079) | Mean Treatment Group (N = 981) | Difference (Control - Treatment) | T-statistic |
|---|---|---|---|---|
| *Views* | 52,655 | 49,998 | 2,658 | .387 |
| *Likes* | 2,307 | 2,069 | 238 | .594 |
| *Shares* | 134 | 160 | -26.1 | -.448 |
| *Reviews* | 162 | 137 | 24.8 | 1.35 |
| *Virtual Tips* | 380 | 216 | 164 | 1.35 |
| *Volume of Existing Reviews* | 162 | 137 | 24.8 | 1.35 |
| *Posivitity of Existing Reviews* | 0.0303 | 0.0305 | -2e-04 | -0.048 |
| *Neutraility of Existing Reviews* | 0.816 | 0.790 | 0.026 | 1.92 |
| *Divergence of Existing Reviews* | 0.103 | 0.0984 | 0.005 | 1.13 |

| | | | | |
|---|---|---|---|---|
| *Type* | 0.493 | 0.489 | 0.004 | 0.170 |
| *Length* | 8.22 | 8.50 | -.276 | -.348 |
| *Age* | 22.3 | 23.1 | -.767 | -.894 |
| *Tag* | 9.09 | 9.18 | -.0820 | -.607 |
| *Followers* | 380 | 216 | 164 | 1.35 |

## 4. Analysis and Results

### 4.1 Model and Results

We specify a DID model to quantify the effect of AIGS:

$$Y_{it} = \alpha_0 + \alpha_1 \cdot Treat_i \cdot After_t + \boldsymbol{X}_{it}\boldsymbol{\beta} + \theta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where $Y_{it}$ denotes the dependent variable, which is the log-transformed value of each of the following: the daily number of views, likes, shares, reviews, and virtual tips of video *i* on day *t*. The time window of our model, i.e., the range of $t$, spans one week before and after the manipulation ([-7, 7]). The variable $Treat_i$ equals one if video $i$ is treated, and zero otherwise. $After_t$ equals one if time $t$ is after the manipulation, and zero otherwise. The coefficient of interaction term $Treat_i \cdot After_t$, $\alpha_1$, of our main interest, captures the effect of AIGS. $\boldsymbol{X}_{it}$ stack the time-varying control variables such as the number of followers of creators, the age of the video, and its square term, which controls for possible nonlinear effects (Zhang and Zhu 2011). Additionally, our model accommodates video-fixed effect $\theta_i$ and time-fixed effect $\delta_t$, including year, month, week, and day of week fixed effects.

**Table 3: Impact of AIGS on Online Video Consumption**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .142*** | .0758*** | .0332*** | .0294** | .0246* |
| | (.0257) | (.0155) | (8.51e-03) | (.0106) | (.0104) |
| $Followers_{it}$ | 1.73e-05*** | -1.25e-06 | -1.23e-05*** | -1.29e-05*** | -8.84e-06*** |
| | (4.30e-06) | (2.59e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0554*** | -.0454*** | -.0152*** | -.0260*** | -.0213*** |
| | (4.34e-03) | (2.62e-03) | (1.42e-03) | (1.76e-03) | (1.72e-03) |
| $Age_{it}^2$ | -1.26e-04** | 1.52e-04*** | 9.63e-05*** | 2.07e-04*** | 1.57e-04*** |
| | (4.41e-05) | (2.66e-05) | (1.46e-05) | (1.82e-05) | (1.77e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |

| | | | | | |
|---|---|---|---|---|---|
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29,363 | 29,363 | 29,363 | 29,363 | 29,363 |
| $R^2$ | 7.4% | 7.0% | 3.7% | 5.1% | 3.6% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 3 presents our estimates of the effects of AIGS. The coefficients of $Treat_i \cdot After_t$ are all positive and statistically significant at the 5% level, suggesting that the inclusion of AIGS enhances online video consumption by improving various engagement activities. Specifically, in comparison to videos in the control group, the presence of AIGS leads to 14.2% more views and a 7.58% increase in likes. In addition, the videos with AIGS are shared by 3.32% more times, and experience increases of 2.94% in reviews and 2.46% in virtual tips (i.e., coins).

**4.2 Validity of the DID Analysis**

Although our randomization checks confirmed the comparability between treatment and control groups prior to the intervention, the validity of the DID analysis depends on the critical assumption of a pre-treatment parallel trend (Angrist and Pischke 2008). To further assess this assumption, we follow previous studies (Gao et al. 2024; Jung et al. 2019; Unal and Park 2023) and employ a relative time model as specified in Equation (2), with the same controls as in Equation (1), to test whether trends of various consumption activities were parallel in the pre-treatment period. Here, $\tau$ represents a period spanning one week before the intervention, with the last pre-treatment day ($\tau$ = -1) serving as the baseline day. The dummy variable $Preperiod_{it}^{\tau}$ equals one if day $t$ corresponds to the $\tau$th day relative to the baseline group, and zero otherwise. Our focus in this estimation is on the coefficients of the $Preperiod_{it}^{\tau}$, particularly $\alpha_{t-7}$ to $\alpha_{t-2}$. If these coefficients are statistically insignificant, this would provide support for the validity of the pre-treatment parallel trend assumption. The results, presented in Table B.1 in Appendix B, confirm that our DID analysis satisfies this assumption, indicating that the treatment effect identified in the DID estimation can be attributed to the AIGS intervention rather than any pre-existing divergence.[10]

[10] Following Jung et al. (2019), we select an alternative pre-treatment day ($\tau$ = -7) as the baseline and the estimation results remain robust.

$$Y_{it} = \alpha_0 + \sum \alpha_\tau \, Preperiod_{it}^{\tau} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \theta_i + \delta_t + \varepsilon_{it} \qquad (2)$$

We also consider the possibility that the observed positive impact is driven by idiosyncratic factors associated with the videos, although we have included video-fixed effects in our model and clustered standard errors at the video level. Following methodologies of previous research (Burtch et al. 2018; Cantoni et al. 2017; La Ferrara et al. 2012), we conduct a random implementation test to address this concern and ensure the validity of our estimation results. Specifically, we randomly reassign the treatment indicators within the data to create a placebo treatment. We then estimate our DID model using the randomly implemented data. We store the coefficient of $\alpha_1$, which indicates the placebo treatment effect of AIGS, and replicate the procedure 1,000 times. The results, presented in Table B.2, show that the placebo treatment effect is not significantly different from zero and confirm that the observed positive effect can indeed be attributed to the AIGS intervention.

## 5. Mechanisms

To gain deeper insights into the impacts of AIGS, in this section, we examine the underlying mechanisms where we argue that AIGS may serve the roles of information and persuasion in shaping video consumption decisions.

### 5.1 Informative Role of AIGS

On online video platforms, information about videos can be initially accessed through titles, descriptions, and tags. However, these elements often offer limited insight into the full scope of the content, resulting in information asymmetry between consumers and creators (Chen and Xie 2005; Liu et al. 2017). The primary function of video titles, for instance, is to capture consumers' attention by highlighting key information (Tafesse 2020). Yet, due to length constraints, titles are often reduced to a succinct sentence or phrase that may not fully represent the video's content. Similarly, video descriptions, though slightly more detailed, are also subject to length limitations, usually offering only a brief summary of the video. Tags, composed of a few keywords, serve to categorize the video and give consumers a broad impression of its subject matter but fail to provide a comprehensive narrative of the content. Additionally, online user-generated reviews have proven to be an effective information source to affect consumer decisions (Chevalier and Mayzlin 2006; Fang 2022). However, the review generation process may be biased by consumers' extreme experiences and existing reviews (Li and Hitt 2008; Feng et al. 2013). In contrast, AIGS present a more informative alternative, providing detailed, neutral, and comprehensive overviews of video content, thereby potentially acting as a supplementary source of information.

To delve into the informative role played by AIGS, we first examine the heterogeneous effects of AIGS in relation to existing user-generated reviews, focusing on three key dimensions of review information: volume, valence, and variance (Dellarocas et al. 2007; Lu et al. 2013). Different dimensions of reviews reflect the richness of information from peer opinions and may moderate the effectiveness of AIGS. Additionally, we aim to examine three moderators related to video features: (1) the nature of the video content (utilitarian vs. hedonic), (2) the length of the video (short-form vs. long-form), and (3) the age of the video at the time of manipulation (late vs. early stage). These features influence the informative needs of videos in different ways and may further influence the effectiveness of AIGS.

**5.1.1 The Effect of AIGS in the Presence of User-Generated Reviews**

***Volume of Reviews*** - Prior research has demonstrated that online user-generated reviews serve as a crucial source of information in shaping potential consumer decisions (Archak et al. 2011; Lu et al. 2013). Although user-generated reviews do not encompass comprehensive narrative of the video content, the presence of a large volume of reviews signifies that consumers have access to more information about the video, assisting them in evaluating the quality of the content and reducing uncertainty. Given that AIGS provide another source of information showcasing video content and coexist with user-generated reviews in our research context, we postulate that the positive impact of AIGS diminishes when substantial information is already available through user-generated reviews.

To test this relationship, we extend Equation (1) by incorporating an interaction term related to the volume of existing reviews into our DID model. As shown in Table 4, the results indicate that while AIGS significantly increase video consumption, their influence on reviews is notably reduced in the presence of a higher volume of existing user-generated reviews (Model 4, p<0.01). This supports the notion that AIGS primarily function as an informative tool. Consumers are often motivated to write reviews by the pleasure of sharing information to help others (Cheema and Kaikati 2010). When writing reviews, consumers consider whether there is already sufficient information to meet potential consumers' informational needs and whether their contribution can add value. Consequently, when numerous user-generated reviews and AIGS provide ample information, the perceived value of additional reviews diminishes, leading to a reduced effect of AIGS on review behaviors. However, regarding other post-viewing behaviors such as likes, shares, and virtual tips, which are not directly tied to conveying content information, the effect of AIGS remains stable. Interestingly, the ability of AIGS to attract initial attention and encourage consumers to watch is enhanced with the volume of existing user-generated reviews, suggesting that the combined information from existing reviews and AIGS helps consumers make more informed viewing decisions.

**Table 4: Heterogenous Effect of AIGS by Volume of User-Generated Reviews**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .125*** | .0735*** | .0371*** | .0377*** | .0279** |
| | (.0267) | (.0161) | (8.83e-03) | (.0110) | (.0107) |
| $Treat_i * After_t * Volume_i$ | 1.21e-04* | 1.63e-05 | -2.86e-05 | -6.00e-05** | -2.40e-05 |
| | (5.02e-05) | (3.03e-05) | (1.66e-05) | (2.07e-05) | (2.02e-05) |
| $Followers_{it}$ | 1.61e-05*** | -1.41e-06 | -1.20e-05*** | -1.23e-05*** | -8.61e-06*** |
| | (4.32e-06) | (2.61e-06) | (1.43e-06) | (1.78e-06) | (1.74e-06) |
| $Age_{it}$ | -.0547*** | -.0453*** | -.0153*** | -.0263*** | -.0214*** |
| | (4.29e-03) | (2.59e-03) | (1.42e-03) | (1.77e-03) | (1.72e-03) |
| $Age_{it}^2$ | -1.35e-04** | 1.51e-04*** | 9.84e-05*** | 2.12e-04*** | 1.59e-04*** |
| | (4.43e-05) | (2.7e-05) | (1.46e-05) | (1.82e-05) | (1.78e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29363 | 29363 | 29363 | 29363 | 29363 |
| $R^2$ | 7.5% | 7.0% | 3.7% | 5.1% | 3.6% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

***Sentiment of Reviews*** - In addition to volume, valence is another key characteristic of user-generated reviews linked to consumption (Chevalier and Mayzlin 2006; Lu et al. 2013). As there are no ratings in our research context, we measured valence through the sentiment of individual reviews. Sentiment analysis typically classifies content as positive, negative, or neutral. In this study, we focus on two dimensions of sentiment: positivity and neutrality. Positivity reflects the degree of positive expressions compared to negative ones, but it does not necessarily indicate how much informational content the reviews convey. Neutrality, on the other hand, refers to reviews that refrain from strong emotional opinions and instead provide more impartial and objective content. In our context, neutral reviews are more likely to contain product- or content-related information, helping to reduce consumption uncertainty. While positivity signals the general attitudes of consumers, neutrality is more indicative of the informational value that assists consumers in making informed decisions. Given the informative role of AIGS, we therefore expect that the influence of AIGS will not be affected by the positivity but will vary with the neutrality of existing user-generated reviews.

Utilizing the Linguistic Inquiry and Word Count (LIWC) tool (Pennebaker et al. 2022), a widely used text analysis method in information systems research (e.g., Clarke et al. 2021; Kokkodis and Ransbotham 2023), we calculated positive and negative scores for each review text, representing the percentage of words related to positive or negative sentiments (Pennebaker et al. 2022). We derived the positivity of each review by subtracting the negative score from the positive score, with higher values indicating more positive reviews. These individual positivity scores were then averaged to obtain the overall positivity for each video. To measure neutrality, we computed the neutrality rate by subtracting the percentages of positive and negative words from one, and then averaged these individual neutrality rates to produce an overall neutrality score for each video.

We added the interaction terms between AIGS and both positivity and neutrality into our DID model, respectively. The results, presented in Table 5 and Table 6, show no heterogeneous effect of AIGS across the average positivity of existing user-generated reviews. However, a higher average neutrality rate diminishes the impact of AIGS on all consumption activities, including views, likes, shares, reviews, and virtual tips. These findings underscore the informative role of AIGS, suggesting that the effects of AIGS are independent of whether consumer opinions are overall positive or negative. Sentiment alone does not convey the informational richness of existing user-generated reviews. Therefore, simply knowing whether peer opinions are more positive or negative does not help potential consumers reduce uncertainty about the content. However, when existing reviews are more neutral and focus on discussing the video content rather than expressing extreme personal emotions, consumers are more likely to rely on this user-generated information for their consumption decisions, even though it may not be as comprehensive as AIGS.

**Table 5: Heterogenous Effect of AIGS by Positivity of User-Generated Reviews**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .157*** | .0822*** | .0341*** | .0267* | .0246* |
| | (.0270) | (.0163) | (8.94e-03) | (.0111) | (.0109) |
| $Treat_i * After_t * Positivity_i$ | -.496 | -.209 | -.0319 | .0890 | -1.25e-04 |
| | (.266) | (.161) | (.0881) | (.110) | (.107) |
| $Followers_{it}$ | 1.72e-05*** | -1.29e-06 | -1.23e-05*** | -1.29e-05*** | -8.84e-06*** |
| | (4.30e-06) | (2.59e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0552*** | -.0453*** | -.0152*** | -.0260*** | -.0213*** |
| | (4.28e-03) | (2.58e-03) | (1.42e-03) | (1.76e-03) | (1.72e-03) |
| $Age_{it}^2$ | -1.29e-04** | 1.51e-04*** | 9.61e-05*** | 2.08e-04*** | 1.58e-04*** |
| | (4.41e-05) | (2.66e-05) | (1.46e-05) | (1.82e-05) | (1.77e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29363 | 29363 | 29363 | 29363 | 29363 |
| $R^2$ | 7.5% | 7.0% | 3.7% | 5.1% | 3.6% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Table 6: Heterogenous Effect of AIGS by Neutrality of User-Generated Reviews**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .367*** | .285*** | .100*** | .187*** | .130*** |
| | (.0543) | (.0328) | (.0180) | (.0223) | (.0218) |
| $Treat_i * After_t * Neutrality_i$ | -.285*** | -.265*** | -.0847*** | -.199*** | -.133*** |
| | (.0604) | (.0364) | (.020) | (.0248) | (.0243) |
| $Followers_{it}$ | 1.80e-05*** | -5.46e-07 | -1.21e-05*** | -1.24e-05*** | -8.49e-06*** |
| | (4.30e-06) | (2.59e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0574*** | -.0473*** | -.0158*** | -.0274*** | -.0222*** |

| | | | | | |
|---|---|---|---|---|---|
| | (4.30e-03) | (2.59e-03) | (1.42e-03) | (1.77e-03) | (1.73e-03) |
| $Age_{it}^2$ | -9.47e-05* | 1.81e-04*** | 1.06e-04*** | 2.29e-04*** | 1.72e-04*** |
| | (4.46e-05) | (2.69e-05) | (1.48e-05) | (1.84e-05) | (1.79e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29363 | 29363 | 29363 | 29363 | 29363 |
| $R^2$ | 7.5% | 7.2% | 3.8% | 5.3% | 3.7% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

***Divergence of Reviews*** - Consumers can derive valuable information from the variance of existing reviews (Sun 2012; Wu et al. 2015). Typically, more divergent and conflicting opinions offer additional perspectives and insights to potential consumers, helping them form a more comprehensive understanding of the content. Given that AIGS provide a structured and objective overview of the video content, their informative ability to enhance video consumption may be less impactful when faced with highly divergent opinions from existing user-generated reviews.

Similarly, we were unable to analyze rating variance as previous studies have done (e.g., Karaman 2021; Sun 2012; Zhao et al. 2012). Instead, we calculated the divergence of reviews based on their positivity, with a higher value denoting more divergent opinions. After obtaining the positivity score of each review, we computed the standard deviation of positivity at the video level. We then incorporated an interaction term between AIGS and this variable into our DID model. The results, shown in Table 7, reaffirm the informative role of AIGS. For all consumption behaviors, including views, likes, shares, reviews, and virtual tips, the effect of AIGS diminishes as the divergence in user-generated reviews increases. While the overall positivity of user-generated reviews does not provide much insight, a review environment with diverse opinions enables consumers to gather more useful information for content evaluation. Therefore, when potential consumers are exposed to more varied discussions among peers, the informative value of AIGS becomes diluted.

In summary, our findings suggest that when user-generated reviews and AIGS coexist, information from humans may substitute the influence of AIGS on various consumption behaviors, especially when neutral discussions or more divergent opinions are available from peer consumers.

**Table 7: Heterogenous Effect of AIGS by Divergence of User-Generated Reviews**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .188*** | .1562*** | .0699*** | .0798*** | .0701*** |
| | (.0336) | (.0203) | (.0111) | (.0139) | (.0135) |
| $Treat_i * After_t * Divergence_i$ | -.469* | -.814*** | -.372*** | -.510*** | -.461*** |
| | (.219) | (.132) | (.0726) | (.0903) | (.0882) |
| $Followers_{it}$ | 1.75e-05*** | -8.39e-07 | -1.21e-05*** | -1.27e-05*** | -8.61e-06*** |
| | (4.30e-06) | (2.59e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0559*** | -.0462*** | -.0156*** | -.0265*** | -.0218*** |
| | (4.28e-03) | (2.58e-03) | (1.42e-03) | (1.76e-03) | (1.72e-03) |
| $Age_{it}^2$ | -1.20e-04** | 1.64e-04*** | 1.02e-04*** | 2.15e-04*** | 1.64e-04*** |
| | (4.42e-05) | (2.67e-05) | (1.46e-05) | (1.82e-05) | (1.78e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29363 | 29363 | 29363 | 29363 | 29363 |
| $R^2$ | 7.5% | 7.0% | 3.7% | 5.1% | 3.6% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

### 5.1.2 Heterogeneous Effects of AIGS Varying with Video Characteristics

***Video Type*** - We first consider the heterogeneous effect of AIGS across different video types. Previous literature has classified products as either hedonic or utilitarian (Botti and McGill 2011; Wertenbroch and Dhar 2000; Khan et al. 2005), and we follow this terminology to categorize video content. Presumably, hedonic content is driven by sensory gratification and experiential pleasure, such as video games or food-related videos. Conversely, utilitarian content is more cognitively demanding, guided by functional and instrumental goals and thus inherently more complex and challenging to process, such as knowledge and technology videos (Crowley et al. 1992; Longoni and Cian 2022; Uzma et al. 2005). Following this classification, we categorize videos from the game and food categories in our experiment as hedonic (labeled as zero), and videos in the knowledge and technology categories as utilitarian (labeled as one).

We created the interaction term between AIGS and the video type and estimated the DID model. The results, presented in Table 8, show that AIGS significantly increase the number of likes, shares, reviews, and virtual tips when the videos are utilitarian in nature. In contrast, AIGS are more effective in boosting consumer views when the videos are hedonic. Since the utilitarian videos are more complex and require larger cognitive efforts to process the information, AIGS assist in this process in helping consumers distill the complicated content. They provide an efficient means of extracting and summarizing the key points of those knowledge and technology videos, reducing the cognitive burden on consumers. As a result, consumers are more likely to engage in deeper post-viewing activities, which demand further cognitive resources and reflection and are more easily to be triggered if AIGS make the content more accessible and comprehensible. In comparison, for hedonic videos, which are generally consumed for entertainment, AIGS tend to serve a different purpose. They help attract more initial views by offering a quick overview that may spark curiosity or excitement. However, once consumers begin watching, the hedonic nature of the content may already fulfill their sensory expectations, leading to less need for deeper consumption behaviors facilitated by AIGS.

**Table 8: Heterogenous Effect of AIGS by Video Type (Utilitarian vs. Hedonic)**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .143$^{***}$ | .0253 | 8.07e-03 | -5.29e-04 | -3.46e-03 |
| | (.0316) | (.0191) | (.0105) | (.0130) | (.0127) |
| $Treat_i * After_t * Type_i$ | -2.08e-03 | .103$^{***}$ | .0510$^{***}$ | .0607$^{***}$ | .0570$^{***}$ |
| | (.0372) | (.0224) | (.0123) | (.0153) | (.0149) |
| $Followers_{it}$ | 1.73e-05$^{***}$ | -1.15e-06 | -1.23e-05$^{***}$ | -1.29e-05$^{***}$ | -8.79e-06$^{***}$ |
| | (4.30e-06) | (2.59e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0554$^{***}$ | -.0454$^{***}$ | -.0152$^{***}$ | -.0260$^{***}$ | -.0213$^{***}$ |
| | (4.28e-03) | (2.58e-03) | (1.42e-03) | (1.76e-03) | (1.72e-03) |
| $Age_{it}^2$ | -1.26e-04$^{**}$ | 1.52e-04$^{***}$ | 9.63e-05$^{***}$ | 2.07e-04$^{***}$ | 1.58e-04$^{***}$ |
| | (4.41e-05) | (2.799e-05) | (1.46e-05) | (1.82e-05) | (1.77e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29,363 | 29,363 | 29,363 | 29,363 | 29,363 |
| $R^2$ | 7.4% | 7.2% | 4.0% | 5.1% | 4.0% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

***Video Length*** - The key function of AIGS is to condense a long video into a short text summary. Therefore, it is essential to understand how the effect of AIGS varies with video length, as consumption difficulty and content complexity are often closely tied to the duration of videos. On online video-sharing platforms, longer videos require consumers to invest more time and effort to fully absorb the content. This increased effort could act as a deterrent for potential consumers, especially those who are time-constrained or seeking quick gratification. In such cases, the incorporation of AIGS allows consumers to swiftly grasp the essence of the original video, thereby reducing their perceived difficulty of consumption and enhancing their overall viewing experience.

To examine the moderating effect of video length, we dichotomized the videos into short-form or long-form categories based on their duration.[11] Based on previous literature, short-form videos are typically defined as those under three minutes, whereas videos exceeding this duration are classified as long-form (Gu and Zhao 2024). Similar to the previous moderators, we added an interaction term to the DID model. The results in Table 9 show that the positive effects of AIGS on daily views and likes are significantly more profound for long-form videos ($p<0.01$). This highlights AIGS's role in providing supplementary information for lengthier content, which can expedite the comprehension process and enable consumers to quickly evaluate whether the content is worth their time investment. By offering a concise summary, AIGS help mitigate consumers' cognitive load when watching original long videos, making them more comfortable in this experience, and thereby gain more likes from consumers. On the other side, the influence of AIGS on more deliberate actions such as shares, reviews, and virtual tips appears to be stable across both short- and long-form videos. These more reflective behaviors often require deeper levels of consumption, suggesting that even though AIGS facilitate initial consumption and viewing experience, the content itself may play a more critical role in driving these behaviors, regardless of the video length. Surprisingly, short-form videos tend to garner more virtual tips in the presence of AIGS, probably because of their brevity and ease of consumption.

**Table 9: Heterogenous Effect of AIGS by Video Length (Long vs. Short)**

| | DailyViews | DailyLikes | DailyShares | DailyReviews | DailyTips |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |

[11] See https://blog.hubspot.com/marketing/video-marketing-report, accessed on 8 October 2024.

| | | | | | |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .0815$^{*}$ | .0341 | .0332$^{**}$ | .0156 | .0446$^{***}$ |
| | (.0335) | (.0202) | (.0111) | (.0138) | (.0135) |
| $Treat_i * After_t * Long_i$ | .105$^{**}$ | .0730$^{**}$ | 6.49e-06 | .0240 | -.0349$^{*}$ |
| | (.0376) | (.0227) | (.0125) | (.0155) | (.0151) |
| $Followers_{it}$ | 1.68e-05$^{***}$ | -1.60e-06 | -1.23e-05$^{***}$ | -1.30e-05$^{***}$ | -8.68e-06$^{***}$ |
| | (4.30e-06) | (2.60e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0553$^{***}$ | -.0454$^{***}$ | -.0152$^{***}$ | -.0260$^{***}$ | -.0213$^{***}$ |
| | (4.27e-03) | (2.58e-03) | (1.42e-03) | (1.76e-03) | (1.72e-03) |
| $Age_{it}^2$ | -1.26e-04$^{**}$ | 1.52e-04$^{***}$ | 9.63e-05$^{***}$ | 2.07e-04$^{***}$ | 1.57e-04$^{***}$ |
| | (4.41e-05) | (2.66e-05) | (1.46e-05) | (1.82e-05) | (1.77e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29,363 | 29,363 | 29,363 | 29,363 | 29,363 |
| $R^2$ | 7.4% | 7.2% | 4.0% | 5.7% | 4.0% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

***Video Age*** **-** We also evaluate the heterogenous effect of AIGS varying with video ages. Typically, video age can serve as a proxy for the amount of existing information available to consumers. Videos at their early stages are evaluated predominantly on the basis of limited information, such as titles, descriptions, and tags. In contrast, videos that have been available for a longer period benefit from accumulating performance metrics such as the accumulated number of views and likes, which offer more robust indicators of the video's popularity (Ryoo et al. 2021). Additionally, more user-generated reviews may be posted on the platform for videos in their later stages. Over time, these signals furnish potential consumers with a clearer picture of the video's appeal and relevance, reducing their reliance on external summaries such as AIGS.

Similarly, we dichotomized the age of video at the time of manipulation into late vs. early stage based on the median value. An interaction term capturing the potentially moderating effects of video age is incorporated into our DID model. Table 10 reports the results. For daily views and likes, the positive effects of AIGS appear to wane with the increase in video age (p<0.001). This indicates that the informative value provided by AIGS is more effective in the early stages of a video's life cycle when there is relatively little information for consumers to rely on. However, for consumption activities that require more deliberation, such as shares, reviews, and virtual tips, the effects of AIGS do not vary across both early and late-stage videos. This suggests that while the informative role of AIGS may fade with time going, their effectiveness in encouraging deeper levels of consumption remains consistent. One possible explanation is that even though the cumulative performance metrics like views and likes can indicate a video's popularity, they do not necessarily provide the detailed content overview that AIGS offer. As a result, consumers may still rely on AIGS when they decide to engage in more reflective or socially visible actions.

**Table 10: Heterogenous Effect of AIGS by Video Age (Late vs. Early)**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .307*** | .125*** | .0265* | .0129 | .0154 |
| | (.0345) | (.0208) | (.0114) | (.0142) | (.0139) |
| $Treat_i * After_t * Late_i$ | -.300*** | -.0900*** | .0121 | .0299 | .0167 |
| | (.0417) | (.0252) | (.0138) | (.0172) | (.0168) |
| $Followers_{it}$ | 1.67e-05*** | -1.41e-06 | -1.23e-05*** | -1.29e-05*** | -8.81e-06*** |
| | (4.29e-06) | (2.59e-06) | (1.42e-06) | (1.77e-06) | (1.73e-06) |
| $Age_{it}$ | -.0610*** | -.0471*** | -.0150*** | -.0254*** | -.0210*** |
| | (4.34e-03) | (2.62e-03) | (1.44e-03) | (1.79e-03) | (1.75e-03) |
| $Age_{it}^2$ | 7.42e-06 | 1.92e-04*** | 9.09e-05*** | 1.94e-04*** | 1.50e-04*** |
| | (4.78e-05) | (2.89e-05) | (1.59e-05) | (1.97e-05) | (1.92e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 29,363 | 29,363 | 29,363 | 29,363 | 29,363 |
| $R^2$ | 7.4% | 7.2% | 4.0% | 5.1% | 4.0% |

Notes: (1) Robust standard errors clustered at the video level in parentheses;
(2) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

### 5.2 Persuasive Role of AIGS

Based on the previous analyses, we have established that AIGS play an important informative role in shaping consumer behaviors, and their effectiveness on video consumption behaviors is contingent on different situations. We now investigate whether the existence of AIGS also persuades consumers in their decision-making, given the notorious hallucination issue of AIGC (Susarla et al. 2023). Previous literature has linked persuasive effect to information credibility (Golden 1977; Sternthal et al. 1978). Recent research has also examined the persuasiveness and credibility of AIGC in propaganda (Goldstein et al. 2024).

Therefore, beyond the basic informative function of AIGS, it is crucial to investigate whether AIGS are trustworthy to potential consumers and how the perceived credibility of AIGS contributes to their effects on consumption behaviors. In this section, we delve into the persuasive role that AIGS may play in online video consumption. We focus on the treatment group in the post-treatment period to explore the extent to which the effects of the AIGS on video consumption are captured by their characteristics in relation to persuasion.

According to prior studies, information credibility and persuasion power are largely guided by its consistency (Golden 1977; Mafael 2021). In our research context, consumers initially learn about videos through the introduction content, such as video title, description, and tags. When they encounter the AIGS, they are likely to compare the information from AIGS with the existing video introduction content to assess its consistency. Therefore, we calibrate the extent of consistency between these two sources and use this measure as one indicator of consumers' perceived credibility of AIGS. To this end, we calculated the content similarity score by the following steps: First, we consolidated the video introduction content (i.e., title, description, and tags) into a single text. We then transformed both the consolidated introduction content and the AIGS into vectors using the term frequency-inverse document frequency (TF-IDF).[12] Finally, we calculated the similarity score by measuring the cosine distance between the two vectors.

In addition to the content similarity score, we utilize the number of likes received by the AIGS as an alternative indicator of its credibility, since consumers normally "like" a review when they perceive it as helpful and trustworthy (Wu et al. 2015). We specify the following panel linear regression model:

$$Y_{it+1} = \alpha_0 + \alpha_1 \cdot Similarity_i + \alpha_2 \cdot No.of\ Likes\ to\ AIGS_{it} + \beta \cdot AIGS\ Features + \gamma \cdot \mathrm{X} + \delta_t + \varepsilon_{it} \qquad (3)$$

where $Y_{it+1}$ represents the log-transformed value of the daily number of views, likes, shares, reviews, and

[12] TF-IDF is a mathematical approach to quantify the importance of each term (word) within a collection of documents. It adjusts the raw term frequency of each term by the inverse document frequency, effectively reducing the weights of the terms that are common across all documents and therefore less indicative of unique content. Intuitively, a word that is highly unique and appears only in a single document retains its raw value. Conversely, a word that is prevalent across many documents is significantly de-emphasized. This method enhances the ability to distinguish between documents based on their specific content.

virtual tips of video $i$ on day $t+1$, serving as our dependent variables to avoid reverse causality. Our focus is the coefficient estimates for $Similarity_i$ and $No.of\ likes\ to\ AIGS_{it}$. To clearly understand how different attributes of AIGS render its effects on video consumption behaviors, we replace the individual fixed effects by a collection of static and dynamic AIGS-related features, such as text length, number of replies, and the rank[13] of AIGS in the review section. In addition, we include variables related to creators (e.g., number of followers), videos (e.g., video type, video length, manipulation age, number of tags, video age, and its square term), and existing user-generated reviews (e.g., volume, sentiment, and divergence), and denote them collectively as $X$. We also include time-fixed effect $\delta_t$, encompassing year, month, week, and day of week fixed effects, consistent with the prior analyses.

The results are reported in Table 11. The effects of $Similarity_i$ are significantly positive on views, shares, reviews, and virtual tips ($p < 0.05$). Overall, when an AIGS aligns closely with the basic video introduction content, consumers tend to engage more in video consumption. Furthermore, our results show that each additional like of the AIGS corresponds to significant increases in all consumption activities. When other consumers signal that an AIGS is helpful and trustworthy through likes, it strengthens the persuasive effect of AIGS. Our exploratory analysis suggests that consumers do use AIGS as a reference for their consumption behavior. When they perceive the content of AIGS as more credible, whether through consistency with existing information or through social cues such as likes, they are more likely to be persuaded to engage in the consumption of the original video.

Interestingly, we observed a non-linear effect of the rank of AIGS. While existing research emphasizes the importance of prominent review positions in influencing behavior (e.g., Liu et al. 2019; Wu et al. 2015), our results suggest that the influence of AIGS initially increases with a higher rank (i.e., posted in a later position) but the effect tends to be mitigated when the AIGS rank becomes too high. The divergent effects of rank on AIGS and user-generated reviews may stem from their differing content nature: AIGS

[13] The Platform utilizes algorithms to rank reviews based on factors including review content, number of likes, and replies received by the review. Therefore, a new AIGS (review) is not necessarily ranked in a later position even if the volume of existing reviews is substantial.

provide objective overviews of video content without actual consumption, whereas user-generated reviews offer subjective evaluations based on personal experiences. It is possible that user-generated reviews contain valuable insights about the original video, and when potential consumers first encounter these reviews and then read the AIGS, they may find the AIGS provide supplementary summaries to enhance their understanding of the video content. Therefore, to maximize the influence of AIGS, it may be beneficial to position some user-generated reviews above the AIGS, while ensuring the AIGS is not ranked so low as to be overlooked by consumers.

**Table 11: Results of Subsample (Treatment Group) Analysis**

| | $DailyViews_{t+1}$ (1) | $DailyLikes_{t+1}$ (2) | $DailyShares_{t+1}$ (3) | $DailyReviews_{t+1}$ (4) | $DailyTips_{t+1}$ (5) |
|---|---|---|---|---|---|
| $Similarity_i$ | 1.177* | .382 | .261* | .243* | .317* |
| | (.460) | (.285) | (.127) | (.112) | (.152) |
| $No.\ of\ Likes\ to\ AIGS_{it}$ | .146*** | .0730*** | .0186** | .0389*** | .0259*** |
| | (.0138) | (9.88e-03) | (6.14e-03) | (7.57e-03) | (7.60e-03) |
| $AIGS\ Length_i$ | 3.96e-05 | 7.99e-05 | -5.33e-05 | 4.49e-05 | 3.48e-05 |
| | (2.21e-04) | (1.37e-04) | (6.12e-05) | (5.40e-05) | (7.33e-05) |
| $No.\ of\ Replies\ to\ AIGS_{it}$ | -.0307 | -.0758 | -9.05e-03 | .103** | -.0296 |
| | (.0771) | (.0541) | (.0312) | (.0341) | (.0383) |
| $AIGS\ Rank_{it}$ | 2.54e-03*** | 1.31e-03* | 6.22e-04 | 1.66e-03*** | 1.87e-03*** |
| | (7.38e-04) | (5.28e-04) | (3.28e-04) | (4.01e-04) | (4.05e-04) |
| $AIGS\ Rank_{it}^2$ | -4.36e-06** | -2.96e-06** | -6.95e-07 | -2.67e-06*** | -2.95e-06*** |
| | (1.44e-06) | (1.03e-06) | (6.34e-07) | (7.66e-07) | (7.83e-07) |
| Control variables | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 7848 | 7848 | 7848 | 7848 | 7848 |
| $R^2$ | 24.5% | 7.3% | 3.1% | 4.3% | 2.2% |

Notes: (1) Standard errors in parentheses;
(2) $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$;
(3) Control variables: a. creators: number of followers; b. videos: manipulation age, video type, video length, number of tages, age, age$^2$; c. existing user-generated reviews: volume, sentiment (positivity and neutrality), and divergence

## 6. Conclusion and Discussion

The advent of generative AI enables us not only to easily generate text, images, and videos but also to quickly grasp the main ideas in long and intricate content with condensed summaries. This study delves into the impact of AIGS on various consumption behaviors with online video content, using a randomized field experiment. We find that AIGS generally enhance online video consumption, and these positive effects are primarily channeled via the informative and persuasive roles played by AIGS.

### 6.1 Theoretical and Practical Implications

While recent research predominantly focuses on the effects of AIGC based on text requests or textual input, our study examines AIGS, which involves complex video-to-text modality transformation, and its application on online video-sharing platforms. By establishing the causal effect and uncovering the underlying mechanisms, our research points out the positive effect of AIGS on video consumption, contributes significantly to the burgeoning literature on generative AI, and provides fresh insights into how AIGS molds content consumption patterns. In today's fast-paced digital environment, consumers increasingly demand condensed content that allows them to quickly grasp complex information. AIGS, in this context, serve as a valuable tool, providing a concise summary of video content without undermining the value of an in-depth consumption experience. Our study is the first to systematically examine the effects of disclosure of content information via AIGS on video consumption behaviors. In doing so, we contribute to the literature on online video consumption by demonstrating how comprehensive content summaries can shape consumer decision-making and enhance various consumption activities.

Notably, we pioneer the investigation of AIGS as a new form of content presented alongside user-generated reviews. Unlike user-generated reviews, which reflect consumers' subjective opinions and sometimes include incomplete disclosure of content, AIGS are produced by generative AI without authentic content consumption and provide more objective and comprehensive summaries of the original content. Nevertheless, the functions of these two types of information are substitutive in certain situations. The informative role of AIGS becomes less pronounced when user-generated reviews already provide extensive insights, such as through a higher volume of reviews, more neutral content, or more divergent opinions. Interestingly, our findings suggest that AIGS are more effective when they are ranked below some user-generated reviews and reveal a nuanced collaboration between content generated by AI and that produced by humans. By introducing AIGS as a novel form of content in the review section and examining their interaction with traditional user-generated reviews in influencing video consumption, our study broadens the scope of UGC literature and sets the stage for future research on AI-generated review content.

Furthermore, our findings highlight the heterogeneous effects of AIGS across different video features, which extend our understanding of the role of AIGS in content consumption and provide valuable guidance for practitioners to enhance video consumption behaviors by strategically leveraging AIGS. For instance, AIGS are more beneficial in attracting initial consumption and improving viewing experience for longer videos and newly posted content, where consumers normally require more information to make informed decisions. Additionally, AIGS are more effective in facilitating post-viewing behaviors for utilitarian videos, which require higher cognitive efforts to process the information. In our context, the summaries of knowledge and technology-related videos provided by AIGS help consumers better understand the material and engage more deeply with the content. Our research therefore underscores the importance of tailoring AIGS deployment based on information needs and cognitive demands of the content.

From a business perspective, as the performance of video content is critical for content creators, marketers, and platforms, our findings offer actionable insights for these stakeholders within the fast-paced digital ecosystem. For content creators and marketers, integrating AIGS into their content strategy presents an innovative and effective tool to boost video performance. By providing reliable and concise summaries, AIGS can meet consumer demand for swiftly understanding complex information, leading to increased content consumption. For platform managers, AIGS provide a novel solution to reduce information asymmetry, where limited video information can hinder consumption. By offering comprehensive video summaries, AIGS enhance user experience and overall consumption behaviors. This improved content performance can attract more advertisers and investors, ultimately benefiting the platform. Overall, our research not only advances the understanding of AIGS as a tool to enhance video consumption but also provide practical implications for optimizing its use alongside user-generated reviews and across different video features. By identifying where AIGS are more effective, we contribute to industry practices by offering actionable insights for platforms seeking to improve consumer engagement and for content creators and marketers aiming to better serve their audiences.

## 6.2 Limitations and Future Research

We acknowledge several limitations in our study. First, while we explore various consumption activities and highlight differences in their effort and deliberate thinking, we do not formally theorize or conceptualize these activities. Our research seeks to provide a comprehensive understanding of the effects of AIGS on various consumption behaviors. Second, we parsimoniously analyze the informative and persuasive role of AIGS independently. While it is possible that consumers first process the information provided by AIGS and are subsequently persuaded by specific content, the design of our randomized field experiment on an online video-sharing platform precluded the simultaneous collection of both video performance data and consumer perception data. As a result, we analyze these functions separately, without addressing their potential interaction. Third, while our findings provide valuable insights into the relationship between AIGS and user-generated reviews, this is merely an initial step in exploring their collaborative mechanisms. Further research is necessary to delve deeper into the content and determine the optimal balance of information disclosure, opinion expression, and positioning between AIGS and user-generated reviews for maximizing their overall impact on content consumption. Given that our primary research question focuses on the impact of AIGS on content consumption, we leave this exploration for future studies. Lastly, we do not manipulate human-generated summaries and compare their effectiveness with AIGS. Our study implicitly assumes that AI can generate summaries at a much lower cost as compared to human beings, without much compromise in the quality. Given similar content quality, the primary difference between AIGS and human-generated summaries is the disclosure of AI identity. Previous literature has extensively investigated how AI identity and anthropomorphic features affect individual decisions (Seymour et al. 2024; Yuan and Dennis 2019). Therefore, this aspect is beyond the scope of our research focus. Instead, we rely on authentic user-generated reviews and examine their interaction with AIGS. Our findings reveal that when consumers include some content disclosure in their reviews (often featured by more neutral sentiments), it will diminish the informative role of AIGS, even though the content disclosure from user-generated reviews might be incomplete or selective.

Future research could further explore several promising avenues. First, this study centers on the impact of AIGS on online video consumption across video-sharing platforms primarily featuring short videos. There is an opportunity to broaden this scope to assess the effect of AIGS on the consumption of longer videos, such as movies and TV dramas on streaming services like Netflix, as well as other digital content forms such as e-books. Additionally, AIGS represents one specific message in the review section in our context, and our investigation of displaying AIGS as a part of reviews is only the beginning. Generative AI can be used to produce human-like reviews for social media content (Wong 2024) and fake user reviews for online applications and industries such as tourism (Koetsier 2024; Meng 2024). Further research on the impact of these AI-generated reviews could deepen the understanding of this emerging domain. Moreover, while using an established and well-performing AI tool for generating all summaries ensured consistency and control over variability, it limited our ability to investigate the nuanced design features that could influence the effectiveness of such tools. Identifying the key features, such as the optimal level of comprehensiveness or detail in summary content, that enhance the effectiveness of AIGS is crucial for understanding the dynamics between AIGC and content consumption. This understanding is also essential for practical purposes, such as improving the design and functionality of generative AI. Finally, it is equally important to investigate the potential adverse effects of AIGS, for instance, whether AIGS contribute to the shortening of consumers' attention spans (Mark 2023). Understanding these potential downsides is key to harnessing the power of AIGS and other forms of condensed content summaries, ensuring that these technologies serve to enrich rather than detract from consumer experience.

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## Appendix A

We apply the DID model to the data from each round of the experiment. The results, presented in Tables A.1 to A.4, show a consistent pattern of the positive impacts of AIGS on video consumption across all rounds. One exception of daily shares in the fourth round was observed, probably due to the limited sample size. Overall, the estimation results demonstrate the robustness of our main findings.

**Table A.1: Results from the First Round**

| **Dependent Variable** | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .149* | .107* | .0713** | .0674* | .102*** |
| | (.0684) | (.0425) | (.0246) | (0.0311) | (.0297) |
| $Followers_{it}$ | 1.84e-05 | 2.00e-05** | -6.90e-06 | -4.54e-06 | -2.84e-06 |
| | (1.02e-05) | (6.30e-06) | (3.65e-06) | (4.61e-06) | (4.42e-06) |
| $Age_{it}$ | .288** | .0830 | .0433 | .0366 | 6.20e-03 |
| | (.0923) | (.0573) | (.0331) | (.0419) | (.0401) |
| $Age_{it}^2$ | -.0152*** | -5.81e-03*** | -1.08e-03** | -.10.8e-03* | -5.64e-04 |
| | (1.12e-03) | (6.96e-04) | (4.03e-04) | (5.09e-04) | (4.88e-04) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 6,975 | 6,975 | 6,975 | 6,975 | 6,975 |
| $R^2$ | 13.7% | 9.6% | 6.5% | 7.0% | 5.7% |
| Parallel Trend | Yes | Yes | Yes | Yes | Yes |

Robust standard errors clustered at the video level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table A.2: Results from the Second Round**

| **Dependent Variable** | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .167** | .132*** | .0519** | -2.73e-03 | .0103 |
| | (.0510) | (.0315) | (.0167) | (.0214) | (.0199) |
| $Followers_{it}$ | 2.31e-05** | -7.32e-06 | -1.50e-05*** | -2.00e-05*** | -1.29e-05*** |
| | (8.20e-06) | (5.07e-06) | (2.69e-06) | (3.44e-06) | (3.20e-06) |
| $Age_{it}$ | .0357* | 1.77e-03 | -4.23e-03 | -.0227*** | -4.27e-03 |
| | (.0154) | (9.51e-03) | (5.05e-03) | (6.46e-03) | (6.02e-03) |

| | | | | | |
|---|---|---|---|---|---|
| $Age_{it}^2$ | -2.27e-03*** | -9.81e-04*** | -1.33e-04** | 1.25e-04* | -4.52e-05 |
| | (1.34e-04) | (8.29e-05) | (4.41e-05) | (5.64e-05) | (5.25e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| *N* | 7,073 | 7,073 | 7,073 | 7,073 | 7,073 |
| $R^2$ | 16.4% | 15.1% | 5.5% | 7.0% | 4.9% |
| Parallel Trend | Yes | Yes | Yes | Yes | No |

Robust standard errors clustered at the video level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table A.3: Results from the Third Round**

| **Dependent Variable** | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .187*** | .0849** | .0462*** | .0427** | .0135 |
| | (.0421) | (.0262) | (.0135) | (.0165) | (.0176) |
| $Followers_{it}$ | 3.24e-07 | -1.63e-05*** | -1.43e-05*** | -1.36e-05*** | -9.26e-06*** |
| | (6.52e-06) | (4.05e-06) | (2.09e-06) | (2.55e-06) | (2.73e-06) |
| $Age_{it}$ | -.101 | -.0108 | -.0485 | -.0388 | -.0821 |
| | (.167) | (.104) | (.0536) | (.0652) | (.0698) |
| $Age_{it}^2$ | 2.36e-04*** | 3.19e-04*** | 8.10e-05*** | 2.17e-04*** | 2.21e-04*** |
| | (7.16e-05) | (4.45e-05) | (2.30e-05) | (2.80e-05) | (3.00e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| *N* | 7,688 | 7,688 | 7,688 | 7,688 | 7,688 |
| $R^2$ | 12.4% | 9.7% | 4.0% | 5.5% | 4.3% |
| Parallel Trend | Yes | Yes | No | No | Yes |

Robust standard errors clustered at the video level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table A.4: Results from the Fourth Round**

| **Dependent Variable** | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| $Treat_i * After_t$ | .132*** | .0156 | -.0247* | .0123 | -.0157 |
| | (.0359) | (.0206) | (.0118) | (.0137) | (.0138) |
| $Followers_{it}$ | 3.85e-05*** | 9.39e-06 | -1.01e-05** | -1.24e-05*** | -1.06e-05** |
| | (8.47e-06) | (4.86e-06) | (2.79e-06) | (3.24e-06) | (3.26e-06) |

| | | | | | |
|---|---|---|---|---|---|
| $Age_{it}$ | -.0670 | -.0343 | .0187 | .0136 | 3.63e-03 |
| | (.0487) | (.0279) | (.0161) | (.0186) | (.0187) |
| $Age_{it}^2$ | 5.03e-04*** | 3.02e-04*** | 9.65e-05*** | 1.77e-04*** | 1.38e-04*** |
| | (4.48e-05) | (2.57e-05) | (1.48e-05) | (1.71e-05) | (1.72e-05) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 7,627 | 7,627 | 7,627 | 7,627 | 7,627 |
| $R^2$ | 11.6% | 5.6% | 10.4% | 3.8% | 2.6% |
| Parallel Trend | Yes | Yes | Yes | Yes | Yes |

Robust standard errors clustered at the video level in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Appendix B**

As shown in Table B.1, the coefficients for pre-treatment periods *t - 7* to *t - 2* are statistically insignificant, indicating that the pre-treatment parallel trend assumption holds in our model.

**Table B.1: Results of Parallel Trend Test**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| **t-7** | .0167 | -.0309 | -.0214 | -3.71e-03 | -.0121 |
| | (.0957) | (.0539) | (.0278) | (.0348) | (.0350) |
| **t-6** | .0184 | -.0780 | -3.65e-03 | -.0274 | -.0304 |
| | (.0931) | (.0525) | (.0271) | (.0339) | (.0341) |
| **t-5** | .0295 | -.0216 | 9.95e-03 | .0188 | .0224 |
| | (.0909) | (.0512) | (.0264) | (.0331) | (.0332) |
| **t-4** | -.0143 | -4.50e-03 | -2.96e-03 | .0122 | .0371 |
| | (.0892) | (.0503) | (.0259) | (.0325) | (.0326) |
| **t-3** | -.0128 | .0144 | 8.89e-03 | 9.91e-03 | .0178 |
| | (.0878) | (.0495) | (.0255) | (.0320) | (.0321) |
| **t-2** | 8.79e-04 | .0408 | .0124 | .0219 | .0198 |
| | (.0868) | (.0489) | (.0252) | (.0316) | (.0318) |
| Video fixed effect | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect | Yes | Yes | Yes | Yes | Yes |
| $N$ | 12883 | 12883 | 12883 | 12883 | 12883 |
| $R^2$ | 6.8% | 4.5% | 1.8% | 2.1% | 2.0% |

Note: (1) Robust standard errors clustered at the video level in parentheses
(2) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

In addition, as shown in Table B.2, the effect of the randomly assigned treatment is not significantly different from zero, indicating that the observed positive impact can be attributed to the AIGS intervention.

**Table B.2: Random Implementation Test**

| | DailyViews (1) | DailyLikes (2) | DailyShares (3) | DailyReviews (4) | DailyTips (5) |
|---|---|---|---|---|---|
| μ of random $\alpha_1$ | -5.01e-04 | 5.40e-04 | -7.67e-04 | 4.50e-04 | -2.84e-04 |
| σ of random $\alpha_1$ | 1.27e-03 | 7.98e-04 | 4.22e-04 | 4.76e-04 | 4.54e-04 |
| 95% confidence interval of random $\alpha_1$ | [-2.98e-03, 1.98e-03] | [-1.03e-03, 2.11e-03] | [-1.60e-03, 6.05e-05] | [-4.84e-04, 1.38e-03] | [-1.17e-03, 6.06e-04] |
| Replications | 1000 | 1000 | 1000 | 1000 | 1000 |