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The Paradox of Sponsorship: How Sponsored Content Affects Creator Credibility and Audience Engagement on YouTube

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ABSTRACT

As influencer marketing becomes a mainstay in the rapidly changing digital advertising landscape, questions remain about how audiences respond to sponsored content on platforms like YouTube, especially in the post-pandemic era. This study investigates whether sponsorship still risks engagement, and whether creator- or content-level attributes can moderate this relationship. Drawing on a dataset of 18,937 videos across 137 U.S.-based YouTube channels between June 2022 and June 2024, the analysis employs fixed-effects regression to isolate within-channel variation in views, likes, comments, and comment sentiment. Contrary to early concerns about "reputation burning," the findings suggest that sponsored content does not significantly reduce behavioural engagement, and may even elicit slightly more positive sentiment among viewers. Further, the results reveal that micro creators, those with smaller followings, demonstrate greater resilience to potential sponsorship fatigue, particularly when their channels regularly feature such collaborations. Visual cues such as thumbnail temperature and brightness also moderate audience reactions, while textual features appear less influential. Together, these findings highlight the complexity of sponsorship dynamics and suggest that authenticity, the sense of community, and visual framing play a crucial role in shaping viewer responses. This research contributes to the growing literature on digital persuasion by integrating parasocial, source credibility, and elaboration likelihood perspectives, offering timely insights for creators, brands, and scholars navigating a maturing content economy.

Key words: Influencer marketing, YouTube, Behavioural analysis, Engagement analysis, Sponsorships

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1 INTRODUCTION

In this chapter, the background and the scope of this research will be introduced, and the research questions and contributions will be outlined.

1.1 Research Background

Influencer marketing grows exponentially with social media evolution. The industry's market size was just $1.4 billion in 2014, climbed $24 billion in 2024, and is projected to reach $32.55 billion in 2025. Social media has become the world's largest advertising channel, which is mainly driven by increasing investment in a variety of creator collaborations[1]. Undoubtedly, sponsored content plays a crucial role in today's social media economy, shaping its nature and leading its evolution. This ecosystem can be broken down into four aspects, namely, platform-wise, creator-wise, brand-wise, and user-wise, for a better understanding of how sponsored content impacts creator credibility and audience engagement levels.

- **Platform-wise**: Social media platforms require sponsored content as it better motivates creators to continue producing on the platform, while also encouraging viewers interested in those creators to stay engaged.
- **Creator-wise**: Brand collaborations enable creators to diversify their income streams while simultaneously enhancing their visibility and reaching broader audience demographics through associations with established brands.
- **Brand-wise**: Social media platforms provide a powerful channel for reaching and engaging with a large, maybe more targeted, audience (Tian, Dew, & Iyengar, 2023), which can help increase brand awareness and recognition[2].
- **User-wise**: Through the sponsored content, users can get to know more products, support the creators they are interested in by engaging more (Bleier, Fossen, & Shapira, 2024).

Geographically, the United States leads the global landscape for influencer marketing with 22.7% of all sponsored posts made by influencers in 2024, totalling 18.9 million posts. Among all the platforms, YouTube (36.7%) remains a stronghold for long-form content and in-depth storytelling, despite the rise of competing platforms like TikTok and Instagram Reels after the pandemic[3]. Hence, analysis of the United States YouTube ecosystem can provide valuable insights into global market trends and offer a comprehensive framework for understanding the trajectory of this dynamic digital landscape.

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[1] Influencer Marketing Hub (25 April 2025), 'Influencer Marketing Benchmark Report 2025', Influencer Marketing Hub, Available at: https://influencermarketinghub.com/influencer-marketing-benchmark-report/ (Accessed by: 5 June 2025)

[2] Hayes, A. (2 June 2025), 'Social Media Marketing (SMM): What It Is, How It Works, Pros and Cons', Investopedia, Available at: https://www.investopedia.com/terms/s/social-media-marketing-smm.asp (Accessed by 5 June 2025)

[3] Influencer Marketing Hub (25 April 2025), 'Influencer Marketing Benchmark Report 2025', Influencer Marketing Hub, Available at: https://influencermarketinghub.com/influencer-marketing-benchmark-report/ (Accessed by: 5 June 2025)

Meanwhile, Post-pandemic shifts have brought a surge of sponsorship activity, especially in the 'Entertainment' and the 'People and Blogs' sectors, since the younger generation is turning to videos, which can comfort emotions instead of following what most people are talking about[4]. As market demands are rapidly changing, it is crucial to understand the underlying logic, and these two content categories will be the subjects of investigation in this research.

1.2 Research Focus and Scope

In this research, different from previous studies which mainly analyse YouTube sponsored content from the brand's perspective, creator-wise and user-wise will be emphasised since they are the main part of the community.

As mentioned, analysing the United States YouTube ecosystem provides valuable insights into global market trends; in addition, the Federal Trade Commission (FTC) asked creators to disclose collaboration details in clear formats in 2019[5], which contributes to the analysis accuracy, so the channels in the US will be targeted.

Audiences in different content might engage differently; moreover, more and more sponsors are flowing into the 'Entertainment' and the 'People and Blogs' recently, and this post-pandemic period trend will be the subject of investigation in this research[6].

YouTube influencers are often categorised by the number of subscribers: nano (1000 or less), micro (1,000–100,000), macro (100,000–1 million), and mega-influencers (more than 1 million)[7]. This breakdown reflects the assumption that audience engagement might be different for creators with different numbers of subscribers (Cheng & Zhang, 2024). To ensure a broad representation of different influence tiers, the sample was stratified by size, engagement, and content relevance to control for heterogeneity.

1.3 Research Questions

The gap in the current literature highlights the need to further explore the dynamics of influencer marketing in the post-pandemic context, particularly from the perspectives of

[4] Allocca, K. (22 June 2022), 'YouTube's Culture & Trends Report: The Rise of Personally-Relevant Pop Culture', Global Director of Culture & Trends, YouTube, Available at: https://blog.youtube/culture-and-trends/culture-trends-report-gen-z-multiformat-shorts-creator-pop-culture/ (Accessed by: 5 June 2025)
[5] Disclosures 101 for Social Media Influencers (1 November 2019), Federal Trade Commission, Available at: https://www.ftc.gov/business-guidance/resources/disclosures-101-social-media-influencers (Accessed by: 26 June 2025)
[6] 'Watching The Pandemic: What YouTube trends reveal about human needs during COVID-19' (n.d.), YouTube, Available at: https://www.youtube.com/trends/articles/covid-impact/ (Accessed by: 8 June 2025)
[7] Sonnenberg, A. (18 September 2021), 'How to Partner With YouTube Micro-Influencers', Social Media Examiner, Available at: https://www.socialmediaexaminer.com/how-to-partner-with-youtube-micro-influencers/ (Accessed by: 9 June 2025)

content creators and their audience. While previous research has mainly focused on brand outcomes or consumer purchasing behaviours, less attention has been paid to how sponsorship affects creator–audience engagement. This study addresses this gap by analysing how sponsored content performs in comparison to non-sponsored (organic) videos within every selected channel, using a dataset of 137 U.S.-based YouTube channels' 18,937 videos in the "People & Blogs" and "Entertainment" categories uploaded between June 2022 and June 2024. A rule-based text classification approach is used to identify sponsored content based on linguistic cues in video descriptions, while sentiment analysis and computer vision tools are applied to extract engagement patterns from comments and thumbnail features.

The research is guided by the following questions:

RQ1: Within each creator's channel, do sponsored videos perform differently from non-sponsored videos in terms of audience engagement?

RQ2: In what ways do sponsorships affect audience engagement metrics, such as view count, like count, comment count, and comment behaviour?

RQ3: To what extent do content-related and creator-level factors, such as channel size, title length, description length, and visual characteristics of thumbnails (e.g., number of people, brightness, colour saturation) influence the magnitude of engagement change?

1.4 Research Contributions

This study makes three key contributions.

Academically, it expands the influencer marketing literature by offering a multi-dimensional analysis of engagement, taking visual and content-based variables into account that have rarely been considered together, and enriches the literature in the post-pandemic period.

Practically, the findings may assist brands in selecting creators more strategically and help creators to better maintain audience relationships when posting sponsored content.

Methodologically, the study applies within-channel comparisons to reduce creator-level heterogeneity and combines natural language processing and visual analysis to offer a robust and nuanced examination of sponsorship effects.

2 LITERATURE REVIEW

This chapter offers a review of the research on influencer marketing on social media platforms, starting from the historical context to the need for a new analysis for the post-pandemic period. Moreover, the framework of this research is introduced and serves as a trigger to highlight the gaps in previous literature, which are also the gaps this study tries to close.

2.1 Introduction to Influencer Marketing on YouTube

2.1.1 Historical Context and Evolution

In the past, brands tended to collaborate with celebrities and projected advertisements on television programmes. This traditional form of endorsement relied heavily on the credibility and popularity of mainstream public figures. In addition, the commercial activities are made through one-way media such as television, radio, and print. Together, it is obvious that these traditional campaigns focused more on exposure than interaction; consequently, the engagement and feedback they can get from the audience would be limited (Freberg, Graham, Mcgaughey, & Freberg, 2011).

However, the notable rise of social media platforms in the early 2000s shifted the celebrity-based endorsement to influencer-driven content. Platforms such as YouTube enabled content creators, mostly non-celebrities, to build their followings based on niche interests, authenticity, and regular interaction with the audience. These influencers engaged in strategic self-presentation, forming ties with viewers, significantly altering how trust and persuasion operated in digital spaces (Marwick, 2015). For example, beauty YouTubers build their brand by consistently sharing their monthly favourites, genuinely recommending products they love, discussing and interacting with audiences, and developing their unique editing style for self-presentation, which helps them accumulate a loyal audience base[8].

This evolution also marked a change in consumer behaviour: people began to see influencers as more relatable and trustworthy than traditional celebrities (Abidin, 2016). The transition from highly polished television advertisements to integrated sponsored content in creator content reflects a broader transformation in marketing. This new ecosystem places audience engagement and perceived authenticity at the core (Phua, Jin, & Kim, 2017).

2.1.2 Theoretical Frameworks

Three main theories were applied as the foundation of this research to grasp the dynamics of influencer marketing and better develop an in-depth understanding of audience behaviours when they receive the sponsored content.

The Elaboration Likelihood Model (ELM) is utilised to better understand how the audience processes the persuasive messages (Petty & Cacioppo, 1986). The model simply identifies persuasive messages into two categories, the central route and the peripheral route. Persuasive messages on the central route are critically judged by the receivers; on the contrary, the messages from the peripheral route persuade receivers to make some impulsive decisions, resulting from factors such as the reputation of the source. In influencer marketing, through a bibliometric analysis of 279 articles in 2022, it was highlighted that the central

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[8] Paish, C. (9 May 2025), '18 entrepreneurs who built a brand on Youtube (and what you can learn from them)', vistaprint, Available at: https://www.vistaprint.com/hub/building-a-brand-on-youtube?srsltid=AfmBOoqcSMNxTIemlt5OXNVI1V8mPF-Tm5RnPpxmSwwJNORS3Oug0t5o (Accessed by: 20 June 2025)

route involves followers thoughtfully and comprehensively processing the content from the influencers, whilst the peripheral route relies more on the reputation and the attraction of the influencers themselves (Srivastava & Saini, 2022). Based on the ELM, a more detailed sentiment analysis can be designed in this study for analysing the comment sentiment in sponsored content and understanding how the audiences process the persuasive messages.

Source Credibility Theory is applied to provide an explanation of how persuasion is formed on social media platforms and driven by influencer characteristics. Influencers' persuasive power is shaped by their expertise, trustworthiness, and attractiveness (Freberg, Graham, Mcgaughey, & Freberg, 2011). An online questionnaire with 341 participants was conducted in 2011, showing that when the audience hits the wall of realisation that they are being advertised to when using social media, the promotional activities influencers take may lead to negative outcomes, such as harming their credibility (Belanche, Casaló Ariño, Flavián, & Ibáñez Sánchez, 2021). Similarly, Source Credibility Theory was applied to this study to deepen comment sentiment analysis results in the sponsored content, seeing if the creator's credibility can be affected by factors such as channel size, like counts and comment counts.

Parasocial Interaction & Micro-Celebrity Theory is used to provide insights into how loyalty is built by the interaction between the audience and creators (Marwick, 2015). The balance between commercial campaigns and organic content is crucial for both brands and influencers. Therefore, once the influencers go beyond self-presentation and harm the tie between them and the audience, a 'Reputation Trade-Off' might happen afterwards (Audrezet, Kerviler, & Moulard, 2018). For example, as a consequence of influencers harming trust, the audience may reduce their passion about the content produced by the specific creator by gradually decreasing the frequency of watching videos, hitting the like button, commenting below the video, or they may even unsubscribe from the channel.

Together, these three frameworks offer a foundation for understanding the psychological and relational mechanisms that may explain changes in audience behaviour when exposed to sponsored content. Based on this foundation, this study can better analyse the complex relationship between creators and the audience, as well as the impacts a sponsorship can bring and therefore provide more solid suggestions to help brands and creators build commercial activities without harming the trust.

2.1.3 Post-Pandemic Digital Shifts

Social media platforms have become central to digital marketing strategies in the past decade, especially in the post-pandemic era, due to their nature of accurately targeting the audience through more personalised formats and efficiently collecting market patterns by analysing the engagement metadata. Whilst Instagram and TikTok have often been at the forefront of influencer commercial campaigns due to their short-form visual content and algorithmic reach (Phua, Jin, & Kim, 2017), YouTube offers a distinct space with strong community ties through long-form videos[9] (Rotman & Preece, 2010).

YouTube has increasingly attracted brands and creators for immersive storytelling by producing long-form videos. In particular, the categories of 'Entertainment' and 'People & Blogs' have seen a significant increase in popularity and sponsorship activity since the COVID-19 pandemic[10]. According to Allocca (2022)[11], younger audiences in the post-pandemic period tend to appreciate videos not simply for information but for emotional comfort and companionship, such as the "#withme" series[12]. These categories, often featuring vlogs, reaction videos, lifestyle diaries, and casual conversations, have thus become hotspots for commercial collaborations.

Interestingly, unlike product-focused categories like beauty and tech, content in these two categories is typically built around creator personality, indicating that the fit between commercial campaigns and the creator's original style is more crucial. Influencers risk trust and audience engagement to place sponsorships into content, searching for the optimal approach under the ever-changing algorithm (Audrezet, Kerviler, & Moulard, 2018). However, after examining 10,000 bootstrap samples, it was highlighted that the sponsored content can be natural when the sponsorship is well-aligned. It can be more spontaneous when the creator maintains transparency and their original style (Boerman, Willemsen, & van der Aa, 2017).

Moreover, the long-tail nature of YouTube videos separates YouTube from other video-related platforms such as Instagram and TikTok due to the algorithm difference. It allows the sponsored content to retain relevance over time, highlighting the need for considering initial bursts of engagement and how engagement evolves afterwards. The algorithm tends to favour channels with deeper engagements, such as more comments, to encourage users to spend more time on the platform (Libai, et al., 2025).

Given this context, this research focuses on YouTube as a platform and on the 'Entertainment' and 'People & Blogs' categories as its empirical scope. These segments offer fertile ground for exploring how sponsorships interact with audience expectations and creator credibility. With the constant increase in sponsorships in these two categories, it becomes critical to understand how and why the engagement reacts to sponsorships, especially as the trend has shifted dramatically since the pandemic.

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[9] Influencer Marketing Hub (25 April 2025), 'Influencer Marketing Benchmark Report 2025', Influencer Marketing Hub, Available at: https://influencermarketinghub.com/influencer-marketing-benchmark-report/ (Accessed by: 11 June 2025)
[10] 'Watching The Pandemic: What YouTube trends reveal about human needs during COVID-19' (n.d.), YouTube, Available at: https://www.youtube.com/trends/articles/covid-impact/ (Accessed by: 11 June 2025)
[11] Allocca, K. (22 June 2022), 'YouTube's Culture & Trends Report: The Rise of Personally-Relevant Pop Culture', Global Director of Culture & Trends, YouTube, Available at: https://blog.youtube/culture-and-trends/culture-trends-report-gen-z-multiformat-shorts-creator-pop-culture/ (Accessed by: 12 June 2025)
[12] 'Watching The Pandemic: What YouTube trends reveal about human needs during COVID-19' (n.d.), YouTube, Available at: https://www.youtube.com/trends/articles/covid-impact/ (Accessed by: 12 June 2025)

2.2 Sponsored Content and Audience Engagement

2.2.1 Sponsorship Transparency and Trust

Transparency is crucial but tricky in influencer marketing, particularly when sponsorships are involved. In previous research, it is notable that sponsorship disclosures can influence the use of persuasion knowledge and also decrease their intention to engage (Boerman, Willemsen, & van der Aa, 2017). However, in some scenarios, when disclosures are clear and consistent, audiences are more likely to maintain trust in the creator and keep the same level of engagement (Evans, Phua, Lim, & Jun, 2017).

In the United States, the Federal Trade Commission (FTC) has set out clear guidelines requiring YouTube content creators to disclose paid partnerships in a specific manner in the description box under the video[13], as shown in Figure 1. Platforms like YouTube have even responded by offering a "Paid Promotion" label to help fulfil this regulatory requirement. It can be used as a way to demonstrate honesty and respect for the viewer, and such transparency measures may even enhance engagement (Jhawar, Varshney , & Kumar , 2023). To reach win-win relationships, disclosure is essential to maintain the trust and the engagement levels for influencers (Audrezet, Kerviler, & Moulard, 2018).

Figure 1: The Relationship with Brands Is Asked to Be Disclosed Clearly in the Description Box

[13] Disclosures 101 for Social Media Influencers (1 November 2019), Federal Trade Commission, Available at: https://www.ftc.gov/business-guidance/resources/disclosures-101-social-media-influencers (Accessed by: 26 June 2025)

2.2.2 Sponsored Content vs. Organic Content

Despite the benefits of disclosure, the sponsored content and organic/ non-sponsored content often perform differently. A growing body of research suggests that sponsorships can increase exposure through the popularity of the brand itself, the platform-level support or the higher production budget, and simultaneously, reduce audience engagement, such as likes, comments, or watch time (Cheng & Zhang, 2024). This phenomenon has been referred to as "reputation burning", where influencers harm their "reputation", such as subscriber number or authority, by repeatedly posting disappointing sponsored content.

Furthermore, sponsored videos may trigger different reactions across various engagement metrics. For instance, the viewership may remain the same at the original level, whilst the like rate and share rate may not. In addition, it is remarkable that the study in 2024, analysing 85,669 videos from 861 creators, points out that the "fit" of the sponsorship is considered to be a significant factor that impacts the engagement level (Cheng & Zhang, 2024). These findings indicate the need for a more nuanced, multi-dimensional understanding of engagement, going beyond simple like-count comparisons.

2.2.3 The Need for Platform-Specific Analysis

Much of the existing literature on influencer sponsorship has focused on platforms like Instagram or TikTok, where content is typically short and has an entirely different algorithm design. However, YouTube offers a video-oriented distinct platform, where videos are often longer, and accumulate views over extended periods (Rotman & Preece, 2010). This long-tail nature means that a sponsored video may continue to generate views and comments beyond its initial upload window[14]. As a result, sponsorship impacts on YouTube videos are more complicated and cannot be seen as the same as on other platforms.

Moreover, the tie between YouTubers and subscribers tends to be stronger due to the nature of the platform (Rotman & Preece, 2010). Content creators on YouTube interact with their audience with videos instead of words, and YouTube allows long-form content to be uploaded, which encourages in-depth storytelling. This strong tie can not only persuade audiences to believe the sponsored content but also heighten their sensitivity to commercial cues (Marwick, 2015). Thus, platform-specific dynamics must be carefully considered when evaluating the impact of sponsored content.

In summary, the existing literature suggests that disclosure clarity as well as sponsorship fit shape the audience reaction. Given YouTube's unique characteristics, such as long-form content, evergreen visibility, and strong subscriber ties, it is crucial to approach its engagement patterns on a platform-specific basis.

[14] Newton, K. (25 July 2022), 'The Complete Guide to YouTube Influencer Marketing', Brandwatch, Available at: https://www.brandwatch.com/blog/complete-guide-to-youtube-influencer-marketing/ (Accessed by: 13 June 2025)

2.3 Multi-Dimensional Engagement Analysis

2.3.1 Different Engagement Metrics React Differently to Sponsorships

Social media engagement is a complex construct encompassing various dimensions. It is essential that engagement should be understood through behavioural, emotional, and cognitive lenses (Karpinska-Krakowiak, 2014). The COBRA (Consumer Online Brand Related Activities) model was therefore proposed as a three-level framework to classify user interactions with brand-related content, indicating that engagement on social media is not only about watching the videos (considered as the first level named Consumption), hitting like button and commenting (considered as the second level named Contribution), but also deeper cognitive and emotional involvement such as writing brand-related articles (considered as the third level named Creation) (Trunfio & Rossi, 2021). Understanding these diverse facets is crucial for accurately assessing the impact of content, especially sponsored material, on audience behaviour.

Hence, it has been argued that traditional metrics such as view counts or like counts may not adequately capture the quality of user engagement (Wu, Rizoiu, & Xie, 2018). In their study, "relative engagement metrics", such as viewer retention and watch time, are introduced in the analysis. The comprehensive engagement metrics not only provide a nuanced understanding of the research but also highlight that video context and channel information can be used to predict the engagement level. Their study suggests that "relative engagement metrics" are more indicative of content quality than the popularity metrics like view counts and like counts.

To further emphasise the complexity of engagement, Facebook pages of YouTube channels focused on video games are studied to observe how the traditional metrics (e.g., like counts) and advanced (e.g., the sentiment analysis of comments) metrics interact (Poecze, Ebster, & Strauss, 2018). They found that lower user-generated activity often correlated with negative sentiment, underscoring the importance of combining these measures to fully understand audience engagement.

The creator's portrayal of emotion and trustworthiness is included in the analysis, delving into the emotional and cognitive aspects of engagement (Stappen, Baird, Lienhart, Bätz, & Schuller, 2022). In their study, it was found that emotional signals, such as arousal (which refers to the intensity of an emotional stimulus) and valence (which refers to the pleasantness or unpleasantness of an experience), within videos can significantly affect engagement indicators. This finding suggests that the emotional content of videos plays a vital role in shaping audience responses and should be considered alongside traditional engagement metrics.

Moreover, the sensitivity of different engagement metrics to sponsorship varies. Most studies suggest that sponsorships may not affect viewership significantly, while like counts and comment counts may have entirely different outcomes. This variability marks the need for a multidimensional approach to engagement analysis, which considers content elements separately.

It is particularly essential and relevant to the video-oriented platform YouTube, where long-form content allows deeper and more complex engagement. By integrating traditional metrics with sentiment analysis and emotional content evaluation, brands and even creators can gain a more accurate understanding of how audiences interact with content, particularly in the context of sponsored material.

2.3.2 Visual Cues in Influencer Content

Visual cues play a central role on social platforms. On YouTube, thumbnails serve as a visual entry to the videos, triggering the audience's expectations and influencing their perceptions of the videos. Interestingly, thumbnails can not only deliver a hint of the content but also impact the click-through rate (which refers to the percentage of users who click on videos after seeing the thumbnails or titles) significantly.

The existence of human faces on Instagram can increase visual attention and perceived credibility (Bakhshi, Shamma, & Gilbert, 2014). It was demonstrated that Instagram photos containing faces are 38% more likely to receive likes and 32% more likely to receive comments. Although this result is based on Instagram data, their findings are still applicable to YouTube thumbnails since they both serve as a trigger competing for attention in dense spaces.

In the context of video content, the emotional valence and arousal levels conveyed in a thumbnail also affect user behaviour after viewers click through. It was found that, on Instagram, excitement, joy, and surprise are more likely to generate clicks and early-stage engagement (Tricomi, Chilese , Conti, & Sadeghi, 2023). This result also resonated with the earlier study, demonstrating that emotional expressions in online video previews can significantly influence user interest and retention (Lewinski, Fransen, & Tan , 2014).

Beyond emotional expression, brightness, saturation, and colour contrast of thumbnails may also impact the likelihood of a video being clicked (Sagheer, Yasir, Safdar, & Shareena, 2024). Thumbnails that include warm, saturated tones and centralised subjects perform better in click-through rates. Hence, it is notable that even tiny choices on thumbnails affect the audience engagement outcomes, making them highly relevant in studies of influencer performance.

From the perspective of influencer marketing, whether thumbnails include the sponsored product matters. For instance, whether the brand is visually present, whether the product is held or used by the creator, or whether the creator appears genuine. These indicators imply the brand-creator fit, highly related to the "reputation burning" (Audrezet, Kerviler, & Moulard, 2018). Thus, visual cues are as vital as engagement metrics when it comes to the understanding of audience behaviour.

2.4 Creator Characteristics and Channel Size

2.4.1 Influencer Tiering and Audience Perception

The relationship between an influencer's follower number and the audience engagement they receive is far from linear. It is shown that engagement rates tend to follow an inverted U-shaped curve, rising to a peak when the follower size reaches mid-tier. With the strongest ties to the audience, mid-tier influencers have the ability to generate higher engagement rates and marketing value (Wies, Bleier, & Edeling, 2022).

This phenomenon implies the existence of a "golden zone" in the influencer market, and also the trade-off between high exposure and strong ties. For example, traditional celebrities offer extensive exposure on one-way media, resulting in a low engagement rate per audience (Jin, Muqaddam, & Ryu, 2019). Similarly, with the increase in follower number, audiences may consider the figure of the creator to be a commercial icon and gradually reduce their trust and willingness to engage day by day (Schouten, Janssen, & Verspaget, 2019).

From a marketing perspective, this implies that more followers do not mean more trust, a stronger tie, and even better performance in commercial campaigns. Hence, more brands tend to seek micro and macro influencers instead of mega influencers for their branding strategies. The number of followers can negatively impact campaigns, especially when sponsorship is overt or lacks personal integration into content, as this decreases the brand's perceived uniqueness and consequently brand attitudes (De Veirman, Cauberghe, & Hudders, 2017).

Thus, considering influencer size is crucial when analysing marketing reaction, as it varies dramatically for influencers in different tiers. Additionally, the audience's reaction can also be affected by content category, content style, tone, and creator characteristics. Comparing creators of different sizes across different content types and audience bases might not be robust enough; therefore, the consistency of creator-specific factors should be considered simultaneously, which serves as core logic answering the third research question of this study.

2.4.2 Within-Creator Comparisons in Engagement

In most of the previous related research, the studies were made by grouping influencers by follower size or content category. Although cross-sectional comparisons between creators have provided useful generalisations by introducing audience composition, content style, and upload frequency (Boerman, Willemsen, & van der Aa, 2017), they are still different, and it is difficult to take all of these factors into consideration at the same time.

To mitigate such biases, controlling the audience base and content style has the potential to offer a more focused alternative. By posting sponsored-like and non-sponsored-like content from two similar accounts, the research is able to keep its audience base and content style nearly the same and get an outcome without the possibility of being affected by content style or the audience base (Colliander & Marder, 2018). This method can be even more effective on YouTube, since creators have shaped their style through publishing histories and consistent audience relationships.

In fact, recent research has begun to recognise the value of within-subject analysis. The within-subject analysis can be seen in the research of sponsorship impacts on Instagram, where results suggest that the impacts are not always negative and sometimes can be content-dependent (Dhanesh & Duthler, 2019). Similarly, the same approach was emphasised and conducted on a sample of 133 Instagram influencers to observe brand effects from platform or personality-driven factors (Tafesse & Wood, 2021). These studies underline that the impact of sponsored content is not uniform, and it can also vary within the same creator's channel, depending on the brand-creator fit, uploading time, and disclosure clarity.

Despite its strength, this approach is still underutilised in empirical research, particularly in the context of YouTube. Given the search-and-recommend-based algorithm, the long-tail nature of YouTube content makes the engagement metrics particularly time-sensitive, which is even more suitable for within-subject design. This evergreen nature allows sustained engagement, and using within-creator comparisons can offer more accurate insights into how sponsorship affects not just visibility, but viewer behaviour and sentiment after the initial upload window.

This study aims to address this gap by systematically comparing engagement patterns across sponsored and non-sponsored videos within the same creator's portfolio. This methodology provides a more robust and precise path forward for influencer marketing research, isolating the qualitative factors and focusing more on the impacts that sponsorships have brought.

2.5 Gaps in the Existing Literature

Despite growing academic interest in influencer marketing, several notable gaps remain in the current literature. This research seeks to address:

1. **More literature focused on short-form or other types of sponsored content on Instagram and TikTok, neglecting the long-form content on YouTube**

Much of the existing literature remains heavily skewed toward Instagram and TikTok, where content performs largely differently from YouTube. The algorithms of Instagram and TikTok specifically favour short-form and visually-driven content (Boerman, Willemsen, & van der Aa, 2017). By contrast, YouTube supports long-form and narrative-driven videos that foster deeper engagement and stronger viewer-creator relationships (Burgess & Green, 2013; Rotman & Preece, 2010). Hence, the parasocial relationships in YouTube communities may react very differently to sponsored content compared to other short-form-video-focused platforms. For example, platform-specific viewer expectations can significantly alter how promotional content is received (De Veirman, Cauberghe, & Hudders, 2017). Also, Instagram and TikTok influencers rely more on the recommendations by the algorithm, whilst YouTube content creators gain partly engagement from audience self-search, making the content more sustained. This field remains undiscovered, and it might limit its explanatory power of the model when previous research tried to draw a cross-platform pattern.

2. The lack of within-channel analysis on YouTube

Moreover, one of the more pressing omissions in analysis in current literature is the lack of within-subject analysis, especially covering sponsored content on YouTube. Most empirical studies adopt cross-sectional approaches, comparing engagement across different creators (Boerman, Willemsen, & van der Aa, 2017; Cheng & Zhang, 2024). While the cross-creator approach allows a broader pattern of the industry or the market, it fails to capture the impacts caused by creator-level factors such as content style, upload consistency, and follower base characteristics. As a result, the outcomes can be biased by those omitted qualitative factors, which are also quite important in social media platform analysis. Thus, within-subject design is now more often conducted in research, isolating the effect of sponsorship on viewer engagement and simultaneously allowing more rigorous outcomes by holding constant individual creator variables (Dhanesh & Duthler, 2019). However, this approach is still largely underutilised in influencer marketing research, particularly on YouTube.

3. The number of large-scale and post-pandemic analyses of sponsored content on YouTube is limited

It is obvious that the COVID-19 pandemic has significantly altered content production and consumption patterns on social media platforms[15], but most studies still rely on pre-2020 data or focus on short-term campaign effects (Cheng & Zhang, 2024). The influencer-based commercial activities are gradually replacing traditional advertisement, and the pandemic has accelerated this transformation. Playing a central role in this transformation, YouTube attracted brands and built a new and promising ecosystem after the pandemic (Bleier, Fossen, & Shapira, 2024). However, few studies have taken advantage of this rich and insightful data from YouTube to examine the new pattern of influencer marketing relating to sponsored content in the post-pandemic period. It is a missed opportunity, as its long-form nature allows for more engagement metrics to be analysed and more audience behaviours to be tracked.

4. The majority of the literature oversimplified engagement metrics

Another critical gap lies in how engagement is measured and conceptualised. It is argued that traditional engagement metrics, such as like count, share count, and comment count, may be too simple to represent user engagement behaviour (Lou & Yuan, 2019). While being useful indicators, they can still fail to capture the impacts caused by qualitative elements of the

[15] Allocca, K. (22 June 2022), 'YouTube's Culture & Trends Report: The Rise of Personally-Relevant Pop Culture', Global Director of Culture & Trends, YouTube, Available at: https://blog.youtube/culture-and-trends/culture-trends-report-gen-z-multiformat-shorts-creator-pop-culture/ (Accessed by: 5 June 2025)

content, the audience's emotional reactions, and the contextual relevance of interaction. Recent works have started highlighting the importance of considering deeper forms of engagement, such as comment sentiment and watch time. As mentioned, YouTube contains rich data on deeper forms of engagement, allowing for more comprehensive analysis. In terms of analysis methods, sentiment analysis tools such as VADER have been employed in related social media research, but their application in influencer marketing is still limited. The combination of deeper-form engagement metrics and emotional sentiment analysis could provide a more robust understanding of how audiences respond to sponsored content.

5. **Not enough of the literature considers thumbnails while analysing the impact caused by content**

Thumbnails, a central component of YouTube's click-through mechanism, are rarely considered in academic studies. It has been shown that visual presentation, such as the presence of human faces, emotional expression, or the colour choices, plays a crucial role for viewers when they are deciding if they are going to watch a video (click through rate) and shapes their perceptions before they click (Tricomi, Chilese , Conti, & Sadeghi, 2023). Given that YouTube users often decide whether to watch a video by its thumbnail, failing to account for the elements on the thumbnail can be a limitation to our understanding of what drives engagement. Moreover, it can be particularly important for observing the difference between sponsored and non-sponsored content since the view count can still be the same, but the like count or share count may not.

6. **Current research offers limited exploration into how follower size impacts the effects of sponsorships**

In previous studies, research considering the follower size of the influencer tends to stop at a surface-level comparison, concluding that smaller influencers are more "authentic" or that larger ones provide more "reach" (De Veirman, Cauberghe, & Hudders, 2017). Whilst some studies categorised influencers into tiers (nano, micro, macro, mega), few explore how creator size interacts with different types of engagement, or even how the audience reacts when they realise they are watching sponsored content. This lack of granularity prevents creators and brands from understanding what the best strategy is for their tiers and their collaboration partners.

The identification of these gaps highlights the need for a targeted methodological approach that can address the specific deficiencies in the existing literature. This study seeks to address these research gaps by applying a combination of theoretical frameworks and machine learning models. Research design will be introduced in the next chapter, which provides a detailed explanation of how these gaps can be closed by employing these models.

3 Methodology

The data collection and preparation process will be presented and thoroughly explained in the first part of this chapter. The research design, such as methodological choices and limitations, is structured by the research questions and will be introduced in the second part of this chapter.

3.1 Data Collection and Preparation

3.1.1 Selection of the Platform

YouTube was chosen for this study since its long-form video nature can provide richer engagement metrics and build a stronger sense of community (Bleier, Fossen, & Shapira, 2024). Moreover, social media has become the world's largest advertising channel, driven by increasing influencer collaboration, and is still expanding at a rapid pace[16]. Hence, YouTube, a distinct platform with more active users on long-form content compared to Vimeo[17] and more global reach than Bilibili[18], serve as a crucial role in understanding the booming and rapidly changing influencer marketing pattern.

3.1.2 Data Sources and Scope

The data for this study were collected from three primary sources: SocialBlade, ChannelCrawler, and YouTube's API/yt-dlp tools.

SocialBlade and ChannelCrawler were used to construct an initial pool of content creators. These platforms allow for filtering based on channel location (mentioned in Introduction §1.2), content category (specifically 'Entertainment' and 'People & Blogs' since audience reaction varies largely among different categories, and they are the two most outstanding categories after the pandemic[19]), and subscriber tiers. From these filters, a list can be generated, ensuring a solid and representative sample across different audience tiers and content categories.

To gather video-level metadata, yt-dlp, an open-source video download and scraping tool, was employed. This tool allowed for the extraction of structured information, including video ID, video title, upload date, view count, like count, comment count, description box content, and thumbnail, as shown in Figure 2 and Figure 3. In parallel, the YouTube Data API v3 was used to retrieve the top-50 publicly accessible comments from each video, subject to the

[16] Influencer Marketing Hub (25 April 2025), 'Influencer Marketing Benchmark Report 2025', Influencer Marketing Hub, Available at: https://influencermarketinghub.com/influencer-marketing-benchmark-report/ (Accessed by: 15 June 2025)
[17] Shelton, I. (20 November 2024), 'YouTube vs. Vimeo: The Key Differences in 2025 (Updated)', Lemonlight, Available at: https://www.lemonlight.com/blog/youtube-vs-vimeo/ (Accessed by: 17 June 2025)
[18] 'Bilibili vs YouTube: For Marketers' (n.d.), GAB China, Available at: https://gab-china.com/bilibili-vs-youtube-for-marketers/ (Accessed by: 17 June 2025)
[19] 'Watching The Pandemic: What YouTube trends reveal about human needs during COVID-19' (n.d.), YouTube, Available at: https://www.youtube.com/trends/articles/covid-impact/ (Accessed by: 8 June 2025)

platform’s 100-comment-per-video limit. Together, these tools provided a comprehensive dataset that enabled both traditional and advanced engagement analysis.

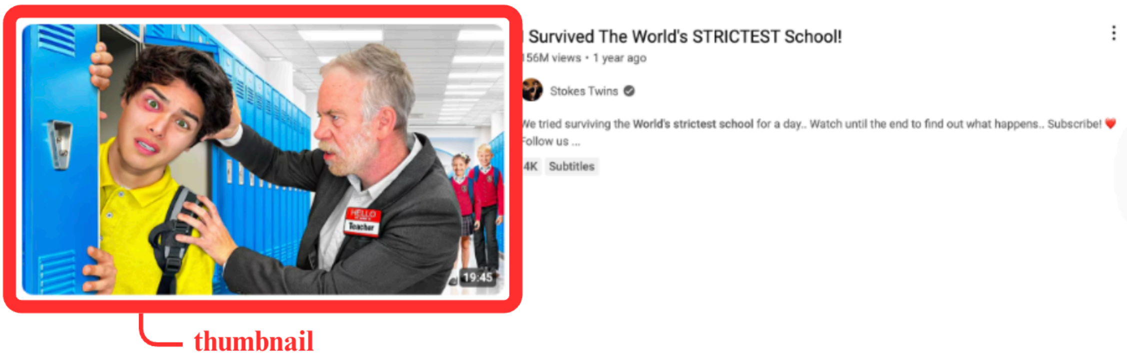


Figure 2: A Thumbnail of a YouTube Video

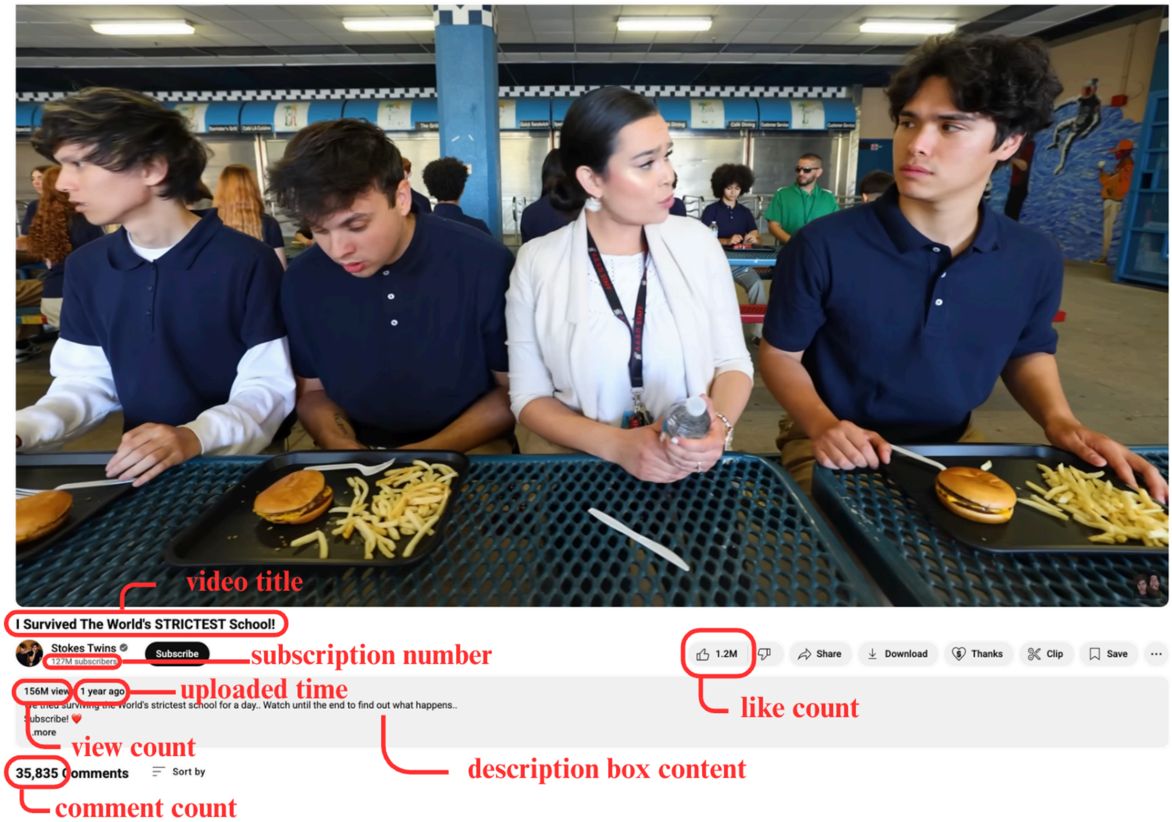


Figure 3: Features Captured from Each YouTube Video

As for the scope of data, the study focuses on videos uploaded between June 2022 and June 2024, a period selected to reflect viewer behaviour in the post-pandemic digital media landscape. This two-year timeframe is chosen to fulfil the need of post-pandemic research on social media audience engagement, and meanwhile ensures that videos have had sufficient time to accumulate views and engagement beyond the initial surge following upload. Given YouTube’s long-tail distribution of viewership, where many videos continue to slowly generate traffic months after publication (Bleier, Fossen, & Shapira, 2024; Rieder, Borra, Coromina, & Matamoros-Fernández, 2023), this timeframe helps capture a more stable and representative level of engagement for each video analysed. Data collection was conducted in June 2025, allowing at least one year of post-upload visibility for the most recent content in the sample.

3.1.3 Sampling

Figure 4 below summarises the filtering and selection process for constructing the final analytical dataset, including 18,937 videos across 137 channels, from the initial pool of over 185,000 videos. As mentioned in Introduction § 1.2, channels were selected based on location and content category due to the FTC request that creators based in the US have to disclose the sponsorship clearly, and audiences in different content might engage differently; however, several selection processes were followed to address the lack of automated tools for filtering channels by engagement visibility and activity level. An 8-step selection process was applied:

1. **Channel Type**: Only public channels would be included to ensure transparency and data availability.
2. **Location**: Channels based in the United States were selected to align with the research scope mentioned in 1.2 Research Focus and Scope.
3. **Content Categories**: This research focused on "Entertainment" and "People & Blogs" sections, as they are the two most popular categories after the pandemic[20].
4. **Subscription Count**: Channels with subscription numbers lower than 1,000 were excluded because they tend to post infrequently and are less likely to receive sponsorship offers (Cheng & Zhang, 2024).
5. **Engagement Visibility**: Videos with visible engagement metrics, such as like counts, were filtered to ensure complete analysis data (as some channels may hide engagement metrics).
6. **Description Box**: Videos with non-empty and English main description boxes were selected to ensure analysis validation.
7. **Activity Level**: Channels that uploaded videos constantly (at least eight videos within the two-year window from 2022) were selected to ensure sufficient analysis data.
8. **Sponsored Status**: To ensure identification of the sponsorship effect within channels, the fixed-effects regression analysis was restricted to channels that included both sponsored and non-sponsored content. Channels with no variation in sponsorship status were excluded from the final regression sample, as such observations do not contribute to the estimation of within-channel differences and can distort standard errors (Wooldridge, 2010).

While the final analytical sample includes 18,937 videos from approximately 137 creators, the study's within-subject design, combined with fixed-effects regression and robustness checks, ensures that the findings are statistically robust. The sample was deliberately

[20] 'Watching The Pandemic: What YouTube trends reveal about human needs during COVID-19' (n.d.), YouTube, Available at: https://www.youtube.com/trends/articles/covid-impact/ (Accessed by: 23 June 2025)

constructed to focus on channels with both sponsored and non-sponsored content, enabling clean estimation of sponsorship effects. Although this selection limits the generalisability to all creators or content genres, it enhances internal validity and causal interpretability within the scope of mid-sized to large-sized U.S. channels in the Entertainment and People & Blogs categories.

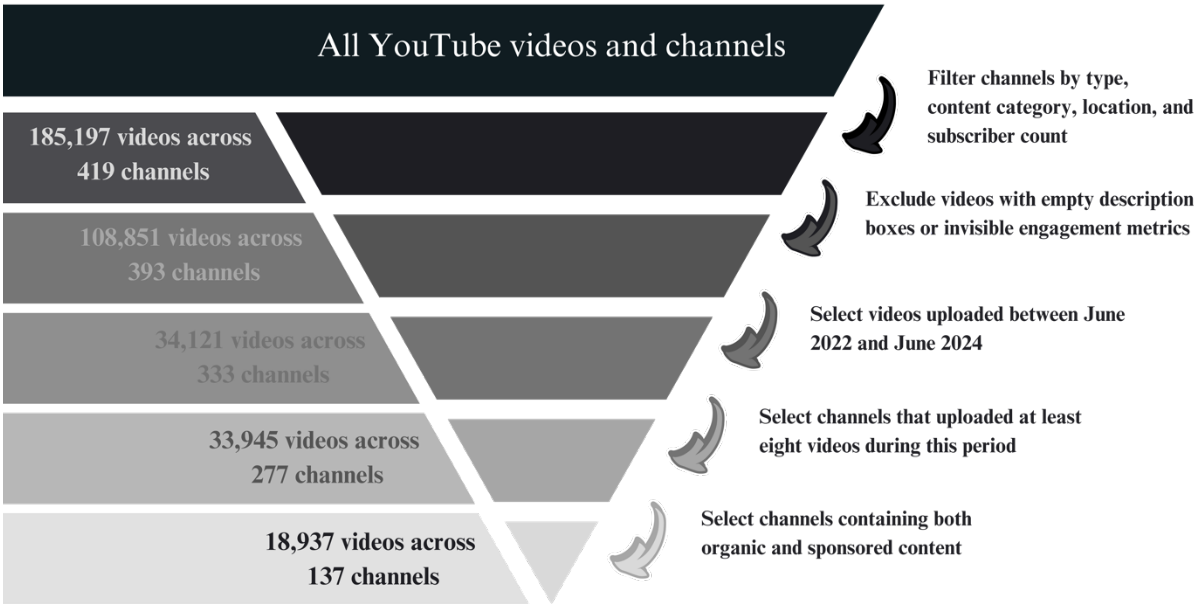


Figure 4: Funnel Chart of Data Filtering Steps

3.1.4 Data Features and Structure

A dataset 'channel_list' was built for automatically fetching the video metadata, including influencer activity and audience engagement:

Table 1: channel_list

Variable	Definition
channel_url	Unique identifier for each channel
category	The content category of the channel, defined by channel's tag, or the source website which are SocialBlade and ChannelCrawler; includes 'People & Blogs' and 'Entertainment'
size	The number of subscribers of channel in June 2025, grouped into three levels 'mega (over 1 million)', 'macro (1 hundred thousand to 1 million)', and 'micro (1 thousand to 1 hundred thousand)'

Three datasets were consequently built from the data in 'channel_list':

Table 2: df_raw

Variable	Definition
video_id	Unique identifier for each video
title	Title of the video
upload_date	Date the video was uploaded to YouTube

view_count	The number of views of the video gained from the date being uploaded to the date being fetched
like_count	The number of likes of the video gained from the date being uploaded to the date being fetched
comment_count	The number of comments of the video gained from the date being uploaded to the date being fetched
description	The content of the description box under the video
thumbnail	Thumbnail of the video
channel_url	Link to dataset 'channel_list'
category	Link to dataset 'channel_list'
size	Link to dataset 'channel_list'

Table 3: comment_sentiment_columns

Variable	Definition
video_id	Link to dataset 'df_raw'
comment_total	The number of popular comments being fetched from the video, capped to 50
pos_comments	The number of positive comments in the comments being fetched, judged by VADER
neu_comments	The number of neutral comments in the comments being fetched, judged by VADER
neg_comments	The number of negative comments in the comments being fetched, judged by VADER
positive_ratio	The ratio of positive comments in total comment being fetched

Table 4: thumbnail_analysis_columns

Variable	Definition
video_id	Link to dataset 'df_raw'
brightness	The brightness of the thumbnail of the video, detected and marked by OpenCV Cascade Classifiers
saturation	The saturation of the thumbnail of the video, detected and marked by OpenCV Cascade Classifiers
temperature	The colour temperature of the thumbnail of the video, detected and marked by OpenCV Cascade Classifiers
face_count	The number of the face in the thumbnail of the video, detected and marked by OpenCV Cascade Classifiers

After all the metadata had been captured properly, several datasets were generated in different preprocessing steps, as shown in Figure 5, and the final dataset 'df_all' was built for the analysis.

- **df**: merge datasets 'df_raw', 'comment_sentiment_columns', and 'thumbnail_analysis_columns' on the key 'video_id'.
- **df_filtered**: Channels and videos were filtered out based on their engagement visibility, description box content, and activity level, as mentioned in 3.1.3 .

- **df_sponsor**: Column ‘sponsored_content_pct’ was added to understand the percentage of sponsored content in the selected videos per channel. A dummy variable ‘is_sponsored’ was created to indicate if the content is sponsored (1) or not (0).
- **df_all**: IQR outlier removal and log transformation were made on ‘view_count’, ‘like_count’, ‘comment_count’, and ‘positive_ratio. Data standardisation was applied to the variables ‘brightness’, ‘saturation’, ‘temperature’, and ‘face_count’. ‘title_word_count’, ‘title_upper_letters’, and ‘description_word_count’ were added to observe more perspectives of how the content of the title and description box impacts.

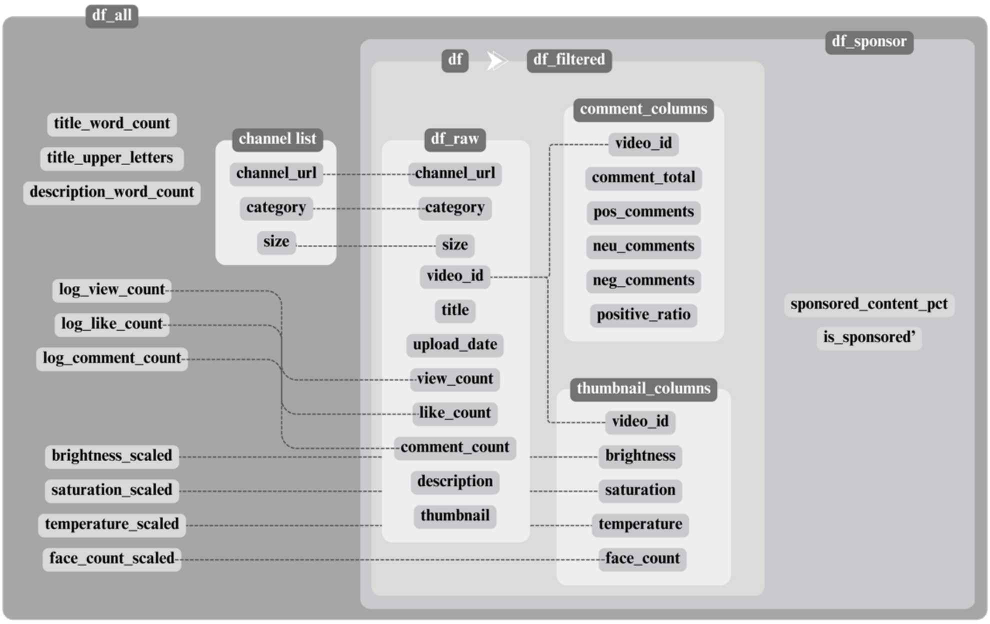


Figure 5: Preprocessing Steps for Final Dataset

3.1.5 Data Preprocessing and Labelling

Before statistical modelling, the dataset underwent several preprocessing steps to ensure comparability and allow for accurate outcomes and explanations.

Firstly, the audience’s comment sentiment was quantified by using VADER (Valence Aware Dictionary and sEntiment Reasoner). VADER is a lexicon- and rule-based sentiment analysis model specifically optimised for short, informal social media texts, such as the comments under Instagram posts (Hutto & Gilbert, 2014). Unlike traditional machine learning models, VADER relies on a human-curated lexicon where each word is associated with a pre-assigned sentiment score. These scores are then adjusted based on contextual rules, such as negations (e.g., “not good”), intensifiers (e.g., “very excited”), and emphatic markers (e.g., ALL CAPS or exclamation points). Mathematically, the overall compound score for a sentence is computed as a normalised weighted sum of word-level valence scores:

$$compound\ score = \frac{\sum_{i=1}^{n} \omega_i \cdot v_i}{\sqrt{\sum_{i=1}^{n} \omega_i^2 + \alpha}}$$

where v_i is the valence score of the ith word, ω_i is the contextual weight based on emphasis or negation, and α is a smoothing constant (default value = 15). The resulting score ranges between –1 and +1, indicating the overall polarity of a sentence.

In this study, VADER was applied to up to 50 top comments for each video. The number and ratio of positive, neutral, and negative comments were calculated accordingly, and the variable positive_ratio was included as one of the engagement metrics. This approach has been validated and applied in multiple studies of social media behaviour. For instance, Poecze, Ebster, & Strauss (2018) analysed the Facebook audience engagement of the top 100 most popular YouTube gamers, indicating the importance of considering the opinion of the masses for a better understanding of the audience feedback.

Secondly, thumbnails were analysed for the visual clues they contain with OpenCV's Haar Cascade Classifiers. This technique is commonly utilised for face detection and image segmentation, and it was applied to this study to quantify the number of faces per thumbnail and basic visual attributes (e.g., brightness, saturation, and colour temperature). Brightness and saturation were computed by converting the RGB thumbnail image into HSV (Hue–Saturation–Value) colour space. The average value of the V channel was taken as a measure of brightness, while the average of the S channel represented saturation:

$$Brightness = \frac{1}{N}\sum_{i=1}^{N} V_i\ ;\ Saturation = \frac{1}{N}\sum_{i=1}^{N} S_i$$

Colour temperature, though less directly measurable from RGB images, was approximated using the relative intensity of red and blue channels. A simple proxy was used:

$$Temperature = \frac{R - B}{G + \epsilon}$$

where ϵ is a small constant to avoid division by zero, and higher values represent warmer tones.

The number of human faces in a thumbnail was estimated using Haar Cascade Classifiers, based on the Viola–Jones algorithm (Viola & Jones, 2001). This method scans the image with a sliding window at multiple scales to detect face-like patterns by evaluating edge and corner contrasts. It has been highlighted that the thumbnail plays an important role in click-through rate and in shaping the audience's expectations (Sagheer, Yasir, Safdar, & Shareena, 2024; Tricomi, Chilese , Conti, & Sadeghi, 2023). The indicators were also standardised to allow for comparison across videos.

Thirdly, view count, like count, comment count and positive comment ratio were log-transformed due to their substantial right-skew in the raw distribution. This transformation is a widely accepted practice in social media analytics, especially when analysing data that follows a long-tail distribution, since it can reduce skewness and satisfy the normality assumption in linear regression (Lou & Yuan, 2019; Osborne, 2010).

Lastly, a binary variable 'is_sponsored' was created to identify whether a video was likely to be sponsored content by scanning their description box under the video for some specific keywords as specified by the FTC. Some keywords, such as 'sponsored', 'paid promotion', and 'advertisement', were checked; to reduce false positives, certain phrases, such as 'not sponsored', 'no ads', and 'not a paid promotion', were also detected and excluded. This rule-based text classification method has been used in prior studies, such as structuring branding strategy for Instagram influencers by analysing follower behaviour, to detect commercial activities in influencer content (Tafesse & Wood, 2021) and provide a scalable method of labelling for large datasets.

Together, these four key preprocessing steps enabled the construction of the dataset (df_all) suitable for the analytical framework in this study, which will be presented in 3.2 Analytical Framework.

3.1.6 Data Limitations

Several data limitations must be acknowledged and should be considered when interpreting the results. First, in the collection term, the data were obtained through publicly available APIs and scraping tools, which restrict access to the platform's backend information. Some informative metrics, such as precise subscriber behaviour and user watch history, cannot be fetched and analysed. Second, VADER in comment sentiment analysis cannot fully understand sarcasm or ironic tone, leading to an oversimplified judgment. Furthermore, creators are grouped into three tiers based on their current channel size (mega, macro, micro), as the subscription number history is restricted by the APIs, and only the current subscription number is available, which may not accurately reflect how channel size impacts it. Finally, the classification of sponsorship is based on the text detection in the description box; although care was taken to avoid false positives, some misclassification or even creator dishonesty is still possible.

3.2 Analytical Framework

3.2.1 Research Design Introduction

A quasi-experimental design was employed in the within-channel analytical framework of this study. Unlike cross-sectional comparisons in most previous research, where sponsored and non-sponsored videos from different creators are compared, this design can better control the unobserved channel-level characteristics. Creator style, audience demographics, and upload schedule can vary greatly across channels. This method in social science research can be a means to reduce selection bias (Angrist & Pischke, 2009).

The core logic of the within-channel design is that each creator serves as their own control. By comparing sponsored and non-sponsored videos from the same channel, the study isolates the effect of sponsorship, minimising the influence of confounding variables. The importance of considering channel-level characteristics has been mentioned more often in recent studies, as it might be a crucial factor influencing sponsored content performance (Tafesse & Wood, 2021).

To operationalise this design, each video is treated as an observation unit, with the sponsorship dummy (i.e., sponsored vs. organic) as the primary explanatory variable. As for the multiple engagement metrics, such as view counts, like counts, comment counts, and the comment sentiment ratio, they would serve as outcome variables. The statistical model incorporates channel-level fixed effects, effectively controlling all time-invariant characteristics of each creator:

$$E_{it} = \beta_0 + \beta_1 \cdot S_{it} + \alpha_i + \varepsilon_{it}$$

Equation 1

In Equation 1, E stands for the engagement metric, and S means the sponsor status; the i here means the index of the channel, and t stands for the index of the individual video. α represents the channel-specific fixed effects, and the ε is the error term. With the control of time-invariant characteristics, the analysis can focus more on the within-channel variation over time (Wooldridge, 2010).

The data pooling across a large sample of channels ensures sufficient statistical power for this study, even if there might be some channels that upload only a relatively small number of videos. By clustering standard errors at the channel level, the model also accounts for within-channel correlation in residuals.

By applying this quasi-experimental within-subject framework, this study aims to capture the correlation, if there is any, that sponsorships bring to the audience engagements and creators' reputation; simultaneously mitigating creator-level confounds that have limited prior influencer marketing research. The detailed model design for each research question in this study will be presented in the next chapter.

3.2.2 Robustness and Limitations

a. Robustness Checks

Firstly, all regressions were estimated with channel-level fixed effects and clustered standard errors at the channel level. These procedures can correct for intra-group correlation and ensure that the inference is not biased by repeated observations within creators. This is especially critical in influencer research, where individual creators may have unique engagement baselines not observable from external metadata (Wooldridge, 2010).

Secondly, a leave-one-channel-out sensitivity test was performed to test for the potential impact of individual channels on the results. For each model, one channel was iteratively excluded, and the coefficient of the 'is_sponsored' variable was re-estimated. The stability of this estimate across iterations ensures that the results are not driven by a small number of highly active or atypical channels.

b. Limitations

Despite the analytical rigour, limitations remain. Although fixed-effects regression and within-subject comparisons reduce omitted variable bias, they cannot account for unobserved, time-varying confounders. For example, changes in YouTube's recommendation algorithm or sudden topical shifts in creator content will not be taken into consideration in this approach.

3.2.3 Summary

A consistent fixed-effects regression framework was applied to this study to examine the effects of sponsorship on audience engagement across multiple metrics. To address the potential impact of unobserved creator-level heterogeneity, a within-channel approach was utilised to better isolate the influence of sponsorship. Various engagement metrics, both traditional and advanced, were included with robustness checks (e.g., clustered standard errors, leave-one-channel-out tests). Moreover, the interaction terms were introduced to evaluate how content- and creator-level characteristics moderate sponsorship effects.

While boosting and ensemble models are highly effective for prediction tasks, this study adopts an OLS-based fixed-effects regression framework due to its interpretability and ability to isolate within-creator variation. Since sentiment scores were pre-processed using rule-based NLP methods, the resulting numeric sentiment ratios can be effectively analysed within a regression framework without requiring additional machine learning layers. Hence, boosting and ensemble models are reserved for future work, serving other research goals.

The empirical strategy in this study aims to provide a clear, rigorous and multidimensional assessment of the relationship between sponsored content and audience behaviour on YouTube.

4 ANALYSIS

In this chapter, the descriptive statistics of the dataset will be first presented. The main results, constructed with the research questions, will be demonstrated and discussed in the last three parts of this chapter.

4.1 Descriptive Statistics

4.1.1 Overview of Dataset Structure

The final dataset of this study is built with 18,937 videos across 137 channels, filtered from the original dataset of 185,197 videos across 419 channels based on the filtering criteria outlined in 3.1.3 Sampling. This filtering approach was used to ensure that each channel could meaningfully contribute to the within-channel comparison design adopted throughout the analysis.

In terms of video volume, the distribution is heavily skewed towards larger creators. In Figure 6, over 80% of the videos in the sample are from “Mega” channels (more than one million subscribers), about 19% of the videos are from “Macro” channels (between 100,000 and one million subscribers), and only a marginal number comes from “micro” channels (fewer than 100,000 subscribers).

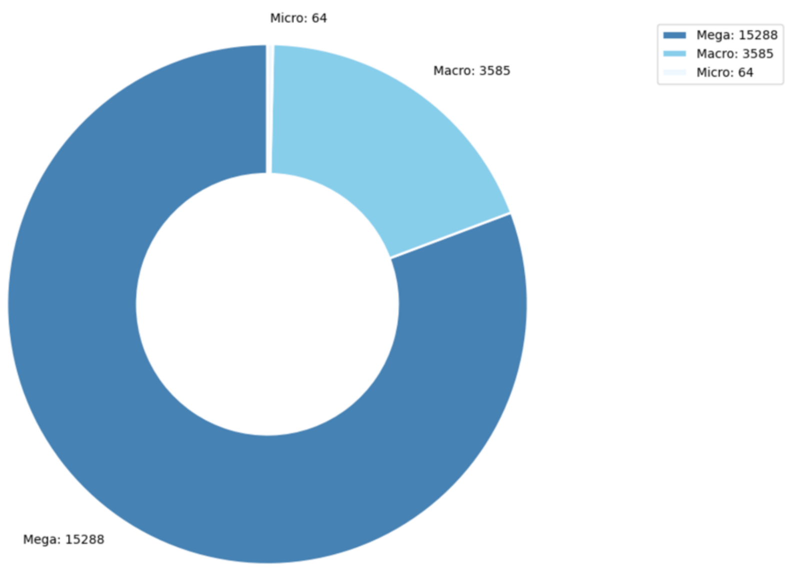


Figure 6: Video Distribution by Channel Size

Similarly, this imbalance can also be found in the channel-level breakdown as demonstrated in Figure 7. While this imbalance may limit the generalisability of some findings to smaller creators, it does reflect the broader sponsorship landscape, where brand partnerships are often concentrated among high-reach accounts in the entertainment field. Further breakdown can be found in Appendix A: Dataset Structure Figure 13 and Figure 14, with video and channel distribution by both category and channel size.

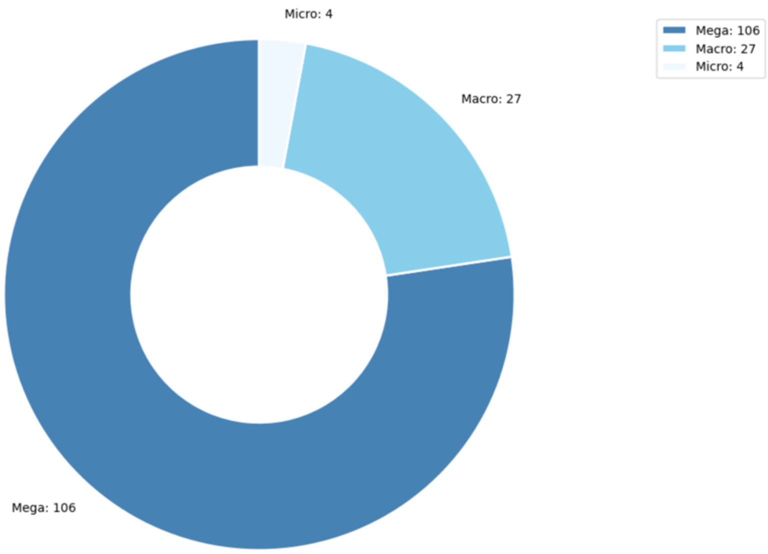


Figure 7: Channel Distribution by Channel Size

Figure 8 below was generated to see if there are specific channels dominating the sample. Moreover, a statistical summary was made to validate the further analysis in this study, as shown in Appendix A: Dataset Structure Table 8. On average, each channel contributes roughly 138 videos to the dataset, with a median of 91. While a few creators contribute over 400 videos, the majority fall between 20 and 150. This variation reflects differences in publishing frequency and also indicates that the dataset retains the within-channel variance, which is important for the fixed-effects modelling strategy employed later.

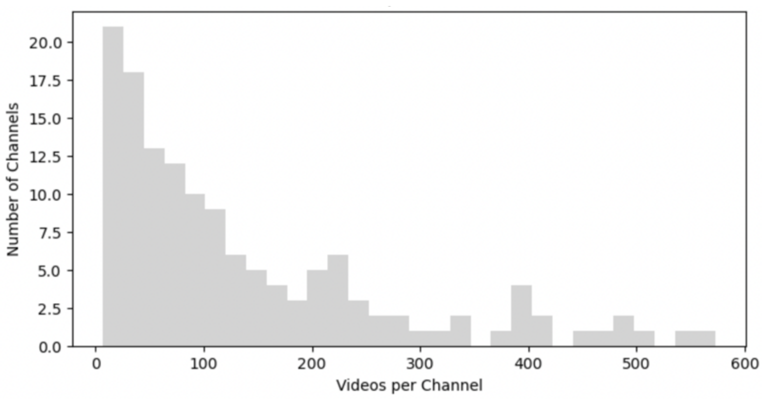


Figure 8: Number of Videos per Channel

To summarise, this sample provides a focused yet sufficiently diverse base for analysing how sponsorship patterns play out across different creator sizes and content outputs, with a particular emphasis on engagement behaviour in large-scale channels.

4.1.2 Distribution of Sponsorship

Within the final dataset of 18,937 videos, over 85% of the videos are classified as “organic”, leaving 14.3% identified as “sponsored”, as demonstrated in Figure 9. The classification was determined based on textual cues found in the description box (see 3.1.5 Data Preprocessing and Labelling), which is systematic but may not fully capture undisclosed or less explicitly marked partnerships.

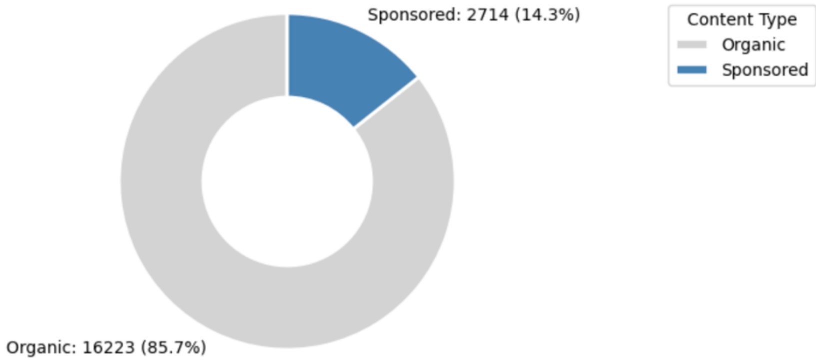


Figure 9: Distribution of Sponsored and Organic Content

For a clearer understanding of sponsored content, Figure 10 was generated. As shown in the figure, nearly half of the sponsored videos come from “People & Blogs” mega channels (44.8%), followed by “Entertainment” mega channels (28.6%). Sponsored videos from micro creators remain marginal, contributing less than 1% of the total sponsored video count. These proportions imply that creators with more subscribers are often prioritised for paid collaborations in lifestyle and entertainment content. More information is provided in Appendix B: Distribution of Sponsorship Table 9 and Figure 15, allowing us to have an early view of the sponsorship ecosystem in the dataset.

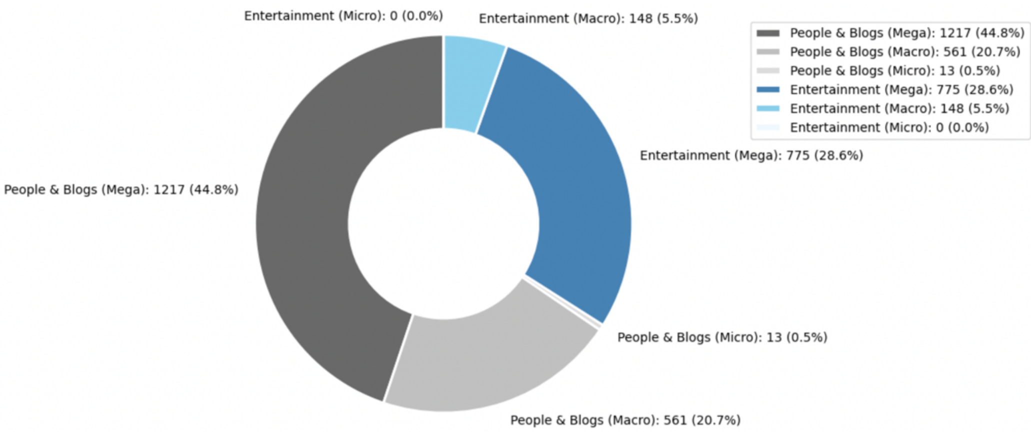


Figure 10: Sponsored Content Distribution by Category and Channel Size

4.1.3 Engagement Metrics: Overall Summary

To provide an initial overview of audience interaction, descriptive statistics were computed across three key engagement dimensions: view count, like count, and comment count. As shown in Appendix C: Engagement Metrics: Overall Summary Table 10, the distribution of these metrics is highly right-skewed, implying that there is a small amount of viral videos. For example, the median view count is around 364,000, whiile the mean exceeds 5.8 million.

To explore whether there are observable differences in engagement between sponsored and organic content, Appendix C: Engagement Metrics: Overall Summary Table 11 presents the average engagement metrics by sponsorship type. On average, it is obvious that organic content has the ability to garner more than 3 times the viewership and like count than sponsored content, and nearly two times in comment count. Additionally, Figure 11 below highlights the possibility that organic and sponsored content might perform differently.

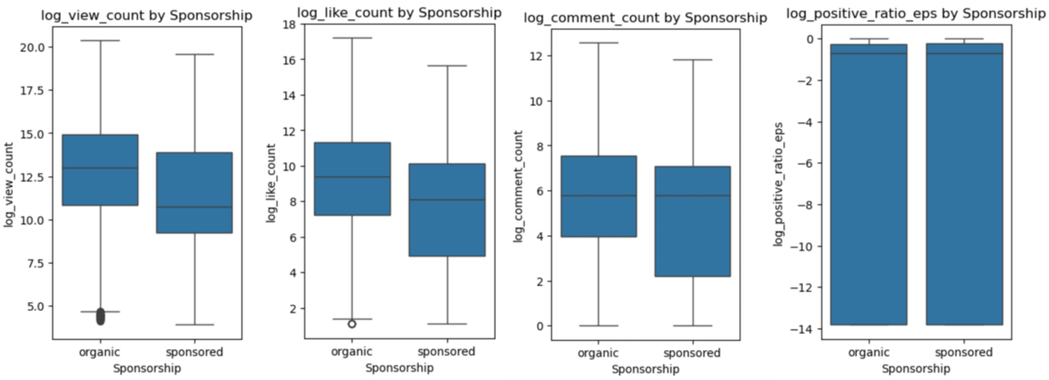


Figure 11: Box Plots of Engagement Metrics (log-transformed)

Hence, these initial observations suggest that sponsorship may be associated with lower average engagement. The following sections will explore whether this trend persists once creator-level fixed effects and video-level characteristics are taken into account.

4.1.4 Visual Inspection of Distributions

Engagement metrics data was visualised to explore its distribution and check for skewness. As shown in Appendix D: Visual Inspection of Distributions Figure 16, view count, like count, and comment count are right-skewed due to the nature of YouTube videos. Therefore, a log-transformation was applied as it is necessary for the model assumption, as shown in Figure 17. However, it is noticeable that the skewness and presence of zeros in the 'positive_ratio' as demonstrated in Figure 18 need to be addressed differently; a log transformation with a small constant, log(positive_ratio + 1e-6) was applied. This approach preserves zero values while reducing the influence of extreme observations.

Moreover, as shown in Appendix D: Visual Inspection of Distributions Figure 19 and Figure 20, other variables like 'saturation', 'brightness', 'temperature', 'face_count', and 'sponsored_content_pct' were scaled for a better and precise comparison.

4.2 Within-Channel Sponsorship Effects (RQ1 & RQ2)

4.2.1 Model Specification Introduction

To investigate whether sponsored content performs differently from non-sponsored content within the same channel, this study employs a fixed-effects modelling approach. By comparing videos within each creator's channel, the analysis controls for unobserved characteristics that remain constant over time, such as editing style and audience composition.

Ordinary Least Squares (OLS) regressions with channel-level fixed effects were applied as primary models. Creator characteristics, such as content style and audience demographics, may significantly impact the results (Wooldridge, 2010). By focusing on within-channel variation, the analysis better isolates the influence, uncovering nuanced effects of sponsorship that cross-sectional methods might miss (Dhanesh & Duthler, 2019). Four outcome variables are examined: view count, like count, comment count, and the ratio of positive comments and each of them is log-transformed before analysis to reduce the influence of extreme values and improve comparability across videos.

Although within-channel sample sizes are relatively small (typically 138 videos), aggregating data across 137 channels nonetheless provides robust statistical power and overcomes limitations associated with single-channel comparisons.

For RQ1, a fixed-effects model was implemented with Equation 1. As mentioned, E_{it} represents one of the engagement metrics for video t in channel i. $sponsored_{it}$ is a binary indicator of sponsorship status for video t in channel i. As for α_i, it serves as the crucial part of this model, an intercept of channel i, such as the audience composition, content style, and the algorithm preference of the channel. ε_{it} is the error term. The coefficient β_1 thus estimates the average effect of sponsorship on engagement within each channel, net of channel-level fixed effects.

To address RQ2, which is an extension of RQ1, a consistent fixed-effects regression framework was adopted. The framework is applied across multiple dependent variables representing distinct dimensions of engagement, including view count, like count, comment count, and comment sentiment ratio. While the underlying model specification remains identical, the interpretation of results is tailored to each specific engagement metric. The same fixed-effects model as in RQ1 was implemented. The core structure of this model remains consistent across outcomes.

For RQ1, the goal was to determine whether there is a significant average difference in engagement between sponsored and non-sponsored videos within each creator's channel. However, in RQ2, the objective shifts toward exploring the relative sensitivity and directional differences across various engagement forms. This dual focus enables a better understanding of how sponsorship influences viewer interaction, not just in quantity but also in quality, and contributes to a growing body of literature calling for a multidimensional understanding of engagement (Lou & Yuan, 2019; Bleier, Fossen, & Shapira, 2024).

4.2.2 Regression Results by Engagement Metric

Firstly, OLS regressions with channel fixed effects were used to analyse the engagement metrics and the results are summarised in Table 5. While the coefficients for views, likes, and comments are not statistically significant, the positive comment ratio reaches the significance level of 5%. Interestingly, the positive coefficient value suggests that although sponsored videos may not see dramatic differences in numerical engagement compared to organic content, viewers may express slightly more positive sentiment in the comments section. However, the coefficient remains small (0.076), implying that sponsorships can increase the positive comment ratio by 7.9% considering the log transformation.

METRIC(log)	COEFF	P-VALUE	R-SQUARED
view count	-0.056061	0.695548	0.845092
like count	-0.241962	0.143831	0.859495
comment count	0.187419	0.252845	0.812628
positive comment ratio	0.076381	0.046825	0.935163

Table 5: Fixed Effect OLS Models Results

For comparison, a simple OLS model without channel fixed effects was also presented in Table 6. In these simple models, coefficients for views, likes, and comments are all significantly negative, and the magnitudes are much larger. This suggests that the sponsored content appears substantially less engaging when the within-channel variations are not being considered. However, it is notable that the R-squared of these models is close to zero, indicating that most of the variation is likely explained by channel-level factors. This reinforces the importance of using fixed-effects modelling to obtain more reliable insight.

METRIC(log)	COEFF	P-VALUE	R-SQUARED
view count	-1.337809	0.000000	0.024993
like count	-1.234195	0.000000	0.021560
comment count	-0.630946	0.000000	0.008134
positive comment ratio	0.050998	0.231311	0.000023

Table 6: Simple OLS Models without Fixed Effects Results

4.2.3 Summary of Within-Creator Variation

The results presented above reveal no strong or consistent evidence that sponsored content leads to a decrease in engagement within the same creator's channel. The only significant association is found in the sentiment ratio, where sponsored content tends to attract slightly more positive comments. These effects are relatively modest, and most of the variation in engagement appears to be driven by creator-specific factors rather than the sponsorship status alone. This underscores the importance of using fixed-effects designs to ensure accurate and reliable insights.

To build on these findings, the next section investigates whether the relationship between sponsorship and engagement is moderated by structural or visual characteristics, such as creator size, content saturation, and thumbnail cues.

4.3 Moderating Factors (RQ3)

4.3.1 Interaction Model Introduction

To have a deeper understanding of the context in which sponsorship operates, beyond the binary distinction of ‘sponsored’ or ‘organic’. RQ3 aims to explore whether certain creator- or content-level characteristics amplify or diminish the observed sponsorship effects. To address this, interaction terms are introduced into the fixed-effects regression models, including two-way interactions such as is_sponsored × face_count and is_sponsored × brightness, and three-way interactions such as is_sponsored × size × sponsored_content_pct. Rather than treating the sponsorship effect as uniform, the models now allow it to vary depending on selected moderators.

In terms of the moderators, they were selected based on their theoretical and empirical relevance in the literature. Channel size labelled based on the subscription number is introduced as a categorical moderator interacting with ‘is_sponsored’, allowing the analysis to test whether sponsorship is more or less impactful among different influencer tiers. Title- and description-box-related features are included since they are most sensitive for promoting video popularity (Hoiles, Aprem, & Krishnamurthy, 2017; De Veirman, Cauberghe, & Hudders, 2017). Thumbnail features are introduced based on research showing that visual cues significantly influence click-through and engagement (Sagheer, Yasir, Safdar, & Shareena, 2024; Tricomi, Chilese , Conti, & Sadeghi, 2023).

These moderators can be categorised in two groups. At the creator level, channel size is included as a key moderator. As discussed in the literature, large channels often face broader but less tightly bonded audiences, which may shape how viewers respond to branded messages. At the content level, video features such as title length and thumbnail design are included. These features often serve as visual entry points for the viewer and may signal the tone, intention, or professionalism of the content. For instance, thumbnails featuring more faces or brighter colours may catch attention, but may also influence perceived authenticity. The models incorporate interaction terms such as is_sponsored × face_count, is_sponsored × saturation, and is_sponsored × title_length, capturing whether the effect of sponsorship depends on these presentation elements.

The analytical specification takes following general form in Equation 2:

$$E_{it} = \beta_0 + \beta_1 \cdot S_{it} +$$

$$\beta_2 \cdot moderator_{it} + \beta_3 \cdot (S \cdot moderator)_{it} + \alpha_i + \varepsilon_{it}$$

Equation 2

The interaction term β_3 here estimates how the effect of sponsorship on engagement varies as a function of the moderator. Fixed effects α_i here continues to control for channel-specific, time-invariant characteristics. Standard errors are clustered at the channel level to account for the potential within-group correlation.

By examining how these moderators interact with the sponsorship variable, the analysis identifies conditions under which sponsorship leads to stronger or weaker engagement. For instance, a significantly negative β_3 in the interaction between 'is_sponsored' and 'title_length' would indicate that longer titles for sponsored videos suffer more engagement loss compared to shorter ones.

This approach addresses a key limitation in the existing literature, where moderation is often discussed descriptively but not empirically modelled (Bleier, Fossen, & Shapira, 2024), and contributes a more rigorous test of heterogeneity in sponsorship effects, aiming to help reveal whether a certain group of creators is more resilient to sponsorship fatigue or a certain sort of content style is more sustainable when commercial activities are introduced.

4.3.2 Results Overview: Channel-Level Moderators

This section explores the moderating effects of channel size and sponsored content percentage to look at how channel-level factors may influence the relationship between sponsorship and audience engagement. In particular, the regression models for each engagement metric incorporate interaction terms between is_sponsored, channel_size, and sponsored_content_pct.

Across all models (full results are demonstrated in Appendix E: RQ3: Channel-Level Moderators), the clearest moderation pattern appears among micro channels, as shown in Table 7. For both view count and like count, the triple interaction term is_sponsored × micro × sponsored_content_pct is statistically significant (p-value = 0.004 and p-value = 0.002, respectively), with a positive coefficient. In contrast, the interaction terms for mega channels are not significant across metrics, though the direction of coefficients generally implies a weak or even slightly negative moderation.

While view count and like count show clear moderation by channel size, the results for comment count and positive sentiment ratio are more ambiguous. Although some coefficients approach 5% significance, particularly is_sponsored × micro × sponsored_content_pct for likes (p-value = 0.059), they remain marginal. No statistically significant moderation effect is found for positive sentiment, indicating that the emotional tone in comments may be less sensitive to such structural factors or is influenced more by content-level variables.

METRIC(log)	INTERSECTION TERM	COEFF	P-VALUE	EFFECT
view count	is_sponsored × micro × sponsored_content_pct	0.0213	0.004	significant
like count	is_sponsored × micro × sponsored_content_pct	0.0148	0.002	significant

comment count	is_sponsored × micro × sponsored_content_pct	0.0259	0.059	marginal
positive comment ratio	is_sponsored × micro × sponsored_content_pct	–0.0020	0.512	no effect

Table 7: Highlight of Import Moderation Effects by Channel Size

4.3.3 Results Overview: Content-Level Moderators

Beyond channel characteristics, this study also explores whether certain content-level attributes influence how viewers respond to sponsored content. Specifically, interaction terms were included between sponsorship and a range of video or thumbnail features, such as thumbnail brightness, saturation, temperature, number of faces, title length, number of uppercase letters, and description word count, to assess whether the sponsorship effect shifts in magnitude or direction depending on visual or textual cues.

Among the visual features (full results are demonstrated in Appendix F: RQ3: Content-Level Moderators), thumbnail temperature emerges as the only consistently significant moderator. For both view count and like count, the interaction terms is_sponsored × temperature_scaled are statistically significant ($p = 0.032$ and $p = 0.021$, respectively), with negative coefficients. This suggests that for sponsored videos, warmer thumbnails may be associated with slightly lower engagement, although the magnitude remains small.

No significant moderation is observed for brightness or saturation in view, like, or comment count models. However, for positive sentiment ratio, the is_sponsored × brightness_scaled interaction reaches significance at the 5% level ($p = 0.049$), with a negative coefficient. This may indicate a subtle reduction in comment positivity for brighter thumbnails in sponsored content, though further validation is needed.

The number of faces in thumbnails, a variable of interest based on prior literature, does not show significant interaction effects across metrics. Similarly, textual features such as title word count, uppercase usage, and description length do not significantly moderate the sponsorship effect. All related interaction terms are statistically insignificant ($p > 0.1$) across metrics, indicating limited explanatory power in this context.

Across all models, engagement with sponsored videos does not appear to be strongly moderated by most visual or textual content features. The only consistent pattern involves thumbnail temperature, with weaker and less consistent evidence for brightness in the sentiment model. These results suggest that sponsorship effects on engagement are likely shaped more by creator-level traits than by content-level packaging.

4.4 Robustness Checks

4.4.1 Alternative Model Specifications

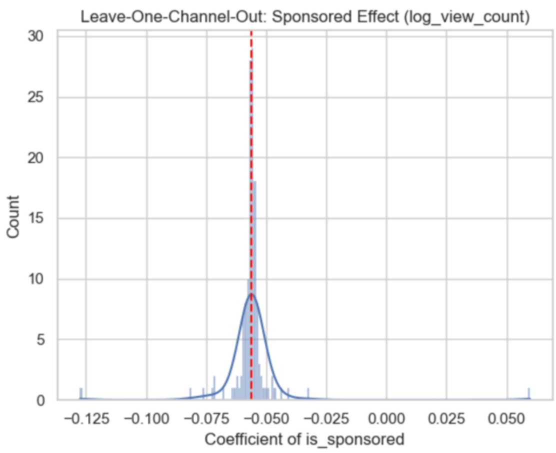
To enhance the reliability of the results, each variable was log-transformed before analysis to reduce the influence of outliers and to improve comparability across videos of varying scales. Also, outlier handling was conducted using the interquartile range (IQR) method. Specifically, videos with extreme values in view, like, or comment counts beyond the 1.5×IQR threshold were excluded. This trimming step reduced the disproportionate influence of viral outliers or unusually low-performing videos. Additionally, to mitigate the instability that may arise from insufficient within-channel variation, only channels with at least eight uploaded videos were included. This threshold was selected to strike a balance between representativeness and statistical stability. Given the study's fixed-effects design, this criterion ensured each channel had adequate variation in video characteristics to estimate within-channel differences meaningfully.

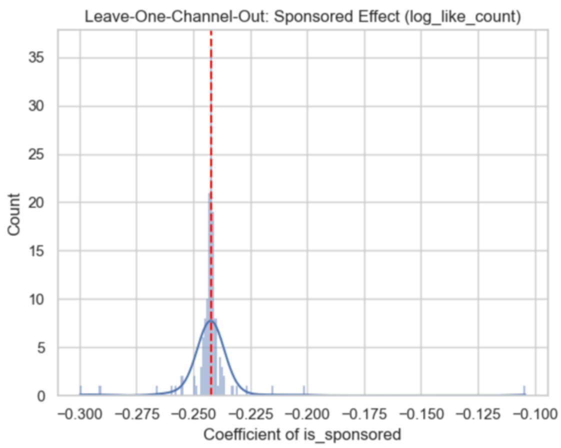
4.4.2 Leave-One-Out Channel Checks

To verify that the observed effects were not driven by a handful of highly influential channels, a leave-one-channel-out analysis was performed. In this procedure, each fixed-effects regression model was repeatedly estimated, systematically excluding one channel at a time. This generates a distribution of the is_sponsored coefficient across all resampled models, offering insight into the stability of results.

As shown in Figure 12, the distributions of the sponsorship coefficients remained narrow and centred closely around the full-sample estimate for all four engagement metrics. The shape of the distributions—tall, symmetric, and sharply peaked—suggests that no single creator had a disproportionate impact on the direction or magnitude of the sponsorship effect.

This check strengthens confidence in the results, indicating that the effects observed are broadly representative across creators, rather than reflecting idiosyncrasies of a few dominant channels. It also reaffirms the value of using a large and diverse panel, where findings are less likely to hinge on outliers or isolated creators.





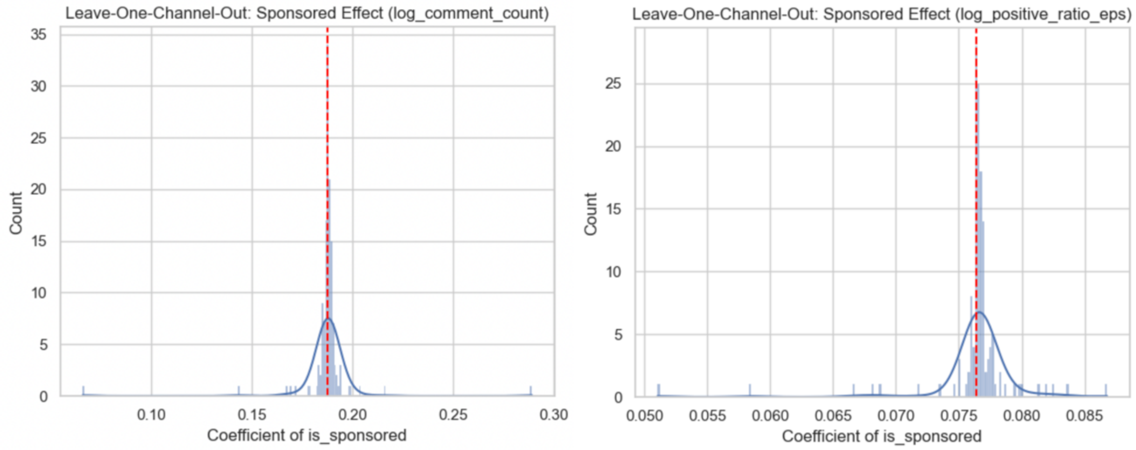


Figure 12: Leave-One-Channel-Out Robustness Check Results

4.4.3 Sample Composition Summary

To ensure the validity of within-channel comparisons, the dataset was restricted to channels that contain both sponsored and non-sponsored videos. This decision effectively removes mono-treatment channels, resulting in a panel that is balanced concerning the treatment variable (is_sponsored). Moreover, a minimum threshold of eight videos per channel was enforced to mitigate concerns related to sparse observations or unstable fixed-effects estimation.

Table 9 in Appendix B: Distribution of Sponsorship reveals that the average channel included in the final sample published 19.8 sponsored videos, with a standard deviation of 52.3. However, the distribution is highly skewed: the median number of sponsored videos per channel is only 4, and 75% of channels have 8 or fewer sponsored uploads. Similarly, the average proportion of sponsored content per channel is 15.9%, with most channels having a relatively low share; half of the creators have less than 5% of their uploads sponsored.

Despite this imbalance in volume, the structural balance across the treatment variable is retained due to the enforced inclusion criteria. That is, every creator in the sample offers both types of content, allowing the fixed-effects model to identify the within-channel sponsorship effect while controlling for overall channel size and activity. Therefore, while the distribution of sponsorship intensity varies across channels, the panel remains analytically balanced to identify engagement differences.

5 Discussion

In this chapter, insightful findings of this study will be thoroughly discussed in the first three sections, followed by the implications for different stakeholders, and limitations as well as future directions in the last section.

5.1 Is Sponsorship Still Risky?

In the pre-pandemic era, YouTube sponsorships were often seen as a double-edged sword since their ability to offer financial opportunities while risking what scholars described as "reputation burning" (Cheng & Zhang, 2024). This study, however, finds a more nuanced post-pandemic landscape by asking: Does sponsored content still weaken audience engagement, and if so, in what ways? (RQ1 & RQ2)

Across the three standard engagement metrics, view count, like count, and comment count, the regression results reveal no statistically significant difference between sponsored and organic videos when comparing content within the same creator's channel. Also, their R-squared values remain high (above 0.81), reflecting the strong explanatory power of channel fixed effects.

This non-significance, however, is not a null result in interpretive terms. Rather, it challenges the long-standing assumption that sponsorship intrinsically harms engagement. Once we control for channel-level characteristics, such as editing style, content flow, and audience composition, sponsorship no longer appears to substantially depress visibility or surface-level engagement. This suggests that much of the "sponsorship penalty" identified in prior studies may have been conflated with structural differences across creators.

Crucially, the positive comment ratio stands out. With a coefficient of 0.076 and a p-value of 0.047, this metric is the only one to show a statistically significant difference. This finding indicates that although viewers may not interact more frequently with sponsored videos, those who do are marginally more likely to leave positive remarks. One interpretation is that audiences recognise the role of sponsorship in sustaining their favourite creators, particularly after a period of global disruption when creators' income streams became less stable. Alternatively, it may reflect a growing norm of strategic transparency where viewers reward creators for authentic brand integration rather than penalising them.

From a psychological perspective, this subtle uplift in sentiment can be viewed through the lens of the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986). While many viewers may not be deeply processing the content's persuasive cues (low elaboration), they rely on peripheral signals, such as their trust in the creator, as a heuristic for whether the message is acceptable. In this case, sponsorship may be seen as a continuation of the parasocial relationship rather than a disruption of it. Additionally, according to Parasocial Interaction Theory (Marwick, 2015), loyal audiences may not interpret sponsorship as a betrayal, but as a necessary and even supportive component of the creator's sustainability.

In summary, the findings point to a post-pandemic sponsorship landscape where audience behaviour is neither uniformly indifferent nor hostile. Sponsorship may no longer be a risky proposition in the traditional sense; rather, its effects are muted, audience-specific, and potentially even constructive when deployed within a stable, trusted creator ecosystem.

5.2 Creator Heterogeneity: The Role of Channel Size

The analysis reveals that the effect of sponsorship on audience engagement is not uniform across creators of different sizes, which is a factor often discussed in both marketing literature and practice (Abidin, 2016; Jin, Muqaddam, & Ryu, 2019). These differences are particularly important when considering the interaction between sponsorship and the proportion of sponsored content within a channel.

Among micro creators, sponsorship appears to have a positive moderating effect on engagement, especially for view and comment counts. This finding aligns with prior studies suggesting that smaller-scale creators tend to cultivate stronger parasocial relationships with their audiences (Labrecque, 2014), resulting in higher tolerance toward commercial messages. Moreover, the increased visibility of sponsored videos in micro channels may signal professional growth rather than overt monetisation, reinforcing trust rather than eroding it.

This observation also resonates with the Source Credibility Theory (Freberg, Graham, Mcgaughey, & Freberg, 2011; Belanche, Casaló Ariño, Flavián, & Ibáñez Sánchez, 2021), which supports that sincerity plays a key role in persuasive communication. In micro creators' case, their perceived closeness to the audience may help preserve credibility even when promoting brands.

Conversely, mega creators show no significant interaction effects, and their coefficients trend slightly negative. This echoes prior research highlighting that larger creators are more likely to be perceived as media entities rather than individuals (De Veirman, Cauberghe, & Hudders, 2017), which can weaken the personal connection and reduce emotional receptivity to branded content, making them have broader reach but experience looser audience bonds and lower tolerance for overt commercial messages. Viewers may also exhibit advertising fatigue, especially if sponsorship frequency is high but not meaningfully integrated into content (Boerman, Willemsen, & van der Aa, 2017).

Importantly, macro creators serve as the reference group; the result suggests a neutral relationship between sponsorship and engagement among macro creators, with no amplifying or mitigating effects from sponsorship frequency.

Taken together, these findings underscore that creator scale is a meaningful moderator of sponsorship impact. Micro creators emerge as particularly resilient, suggesting that sponsorship may no longer be perceived as a "sell-out" moment but rather a natural part of content sustainability. For mega creators, however, sponsorship saturation may require more thoughtful integration to avoid disengagement. This has direct implications for both theory and practice: the effectiveness of influencer marketing depends not only on content quality or disclosure strategy, but also on the structural context of the creator–audience relationship.

5.3 Content Cues as Contextual Amplifiers

Beyond structural channel-level differences, this study finds that content-level cues can subtly shape how viewers respond to sponsored videos. While most individual interaction terms are not statistically significant, several patterns emerge that warrant closer theoretical reflection.

5.3.1 Visual Dimensions

Firstly, brightness and temperature appear to interact with sponsorship status in affecting comment sentiment. In particular, brightness shows a statistically significant negative interaction with sponsorship on the positive comment ratio, suggesting that overly bright thumbnails may backfire in sponsored content, perhaps due to perceptions of excessive commercial polish or emotional inauthenticity. This echoes prior US-based social media research, which finds that visually “warm” or overproduced cues can reduce perceived authenticity in influencer marketing, especially when promotional activities are involved (Kim & Kim, 2022).

Likewise, as shown in Appendix G: Visual Cues as Contextual Amplifiers colour temperature, Figure 21 shows a marginally significant interaction with view count and like count. Colder-toned thumbnails tend to correlate with lower engagement in sponsored content, possibly because they suppress affective resonance. This finding aligns with theories of embodied cognition, which suggest that viewers associate warm colours with emotional approachability and cold tones with distance or detachment (Williams & Bargh, 2008).

Secondly, while face count does not show statistically significant interaction effects, the directionality is worth noting. Notably, coefficients are consistently positive across metrics, which resonates with the notion that human presence in thumbnails fosters emotional connection (Bakhshi, Shamma, & Gilbert, 2014), and may serve as a softening mechanism for sponsored content. Although not definitive here, future work with more nuanced facial analysis (e.g., expression, gaze direction) could provide deeper insights.

5.3.2 Textual Dimensions

Textual characteristics such as title length, description length and use of uppercase letters in titles were also examined, yet yielded limited evidence of interaction. Still, the results provide this study with the fact that, within the same channel, the length of the title as well as the description box and how creators emphasise the titles make limited differences in the performance of organic and sponsored content.

This aligns with the Elaboration Likelihood Model (Petty & Cacioppo, 1986): when viewers recognise peripheral cues (like visual tone) that contradict their preferred content type, persuasion may backfire, especially in a sponsored setting. In contrast, when textual and visual elements remain congruent with the channel’s usual aesthetic, audience tolerance may increase.

5.4 Implications for Stakeholders

5.4.1 For Brands: Aligning Creator Strategy with Promotional Objectives

The findings suggest that brands may benefit from adopting a more nuanced creator strategy that goes beyond the traditional emphasis on reach. While partnering with mega creators remains effective for achieving broad exposure, the analysis shows that such content may not consistently yield stronger engagement or sentiment, which may not be the goal of the commercial activities. In contrast, micro creators, especially those with a higher share of sponsored content, appear to foster more positive viewer responses, potentially due to stronger audience bonds or clearer communication norms.

This indicates a potential trade-off. When brand objectives centre on awareness and exposure, larger channels may still serve that purpose. However, if the goal is to cultivate affinity, trust, or eventual conversion, collaborations with smaller creators may yield greater returns. Rather than prioritising absolute reach, it may be more strategic to consider the depth and authenticity of creator–audience relationships when selecting promotional partners.

5.4.2 For Creators: Preserving Trust While Monetising Content

For creators, the findings offer an encouraging message that sponsorship no longer automatically reduces audience engagement. Across multiple metrics, sponsored content performs comparably to organic content, and in some cases, such as comment sentiment, even slightly more positively. This may reflect a broader shift in audience perception, where sponsorship is now seen as a natural part of the YouTube ecosystem, rather than a disruption.

Still, this outcome seems to depend on the strength of the creator–audience bond. Micro creators, in particular, show greater resilience in the face of increased sponsorship exposure, suggesting that loyal audiences may view such collaborations as well-earned rather than commercialised. This raises a notable takeaway, which is that as creators grow, the challenge lies in scaling reach without diluting the community. Preserving a sense of familiarity, transparency, and stylistic coherence becomes even more important as follower counts increase. Replying to comments, disclosing the relationships with brands, running Q&A sessions or hosting offline/online events are helpful for fostering the sense of comminuty within channel.

Visual and textual signals also matter. While the effects of thumbnail design or title structure are often subtle, they can shape how audiences perceive authenticity. Creators may wish to consider how their choices, such as tone, colour palette, and message placement, contribute to the broader narrative of trust.

5.5 Limitations and Future Directions

5.5.1 Data limitations: Surface-Level Signals and Observational Constraints

This study relies on publicly accessible data collected via the YouTube API and yt-dlp, including view counts, like counts, comment sentiment, and thumbnail-level features. While these indicators offer useful approximations of audience engagement, they remain limited to surface-level signals. Platform-visible metrics often mask more complex behavioural patterns, such as actual watch duration, click-through rates, or ad retention, which are not available without backend access (Cheng & Zhang, 2024).

The comment sentiment analysis, although enhanced by VADER (Hutto & Gilbert, 2014), is constrained by its lexical approach and its focus on a sample of up to 50 top comments per video. As a result, it cannot fully account for sarcasm, irony, or nuanced affective shifts that may emerge in long-form user responses. More sophisticated models, such as transformer-based sentiment classifiers, could provide richer insights and capture sentiment shifts at a more granular level.

5.5.2 Labelling and Measurement Challenges

The identification of sponsored content was based on keyword-matching within video descriptions. While this technique is pragmatic and aligned with practices in prior research (Dhanesh & Duthler, 2019), it remains vulnerable to classification errors. Creators who disclose sponsorship verbally or embed mentions in more subtle language may not be detected. This misclassification could introduce noise into the analysis, particularly if disclosure style varies systematically across creator groups.

In terms of modelling, the fixed-effects regression framework controls for time-invariant characteristics at the channel level (Wooldridge, 2010). However, the analysis remains correlational rather than causal. Although within-channel comparisons reduce bias from unobserved heterogeneity, they cannot rule out reverse causality or omitted variables that shift over time. Future studies could consider designs that enable stronger causal identification, such as natural experiments, staggered policy changes, or instrumental variable strategies.

5.5.3 Scope and Generalisability

The study's focus on U.S.-based creators in the "People & Blogs" and "Entertainment" categories was designed to ensure analytical consistency. However, this scope also limits generalisability. Norms of sponsorship disclosure, viewer expectations, and platform culture differ across countries, languages, and content verticals (De Veirman, Cauberghe, & Hudders, 2017). The patterns observed in this dataset may not apply to creators operating in non-English markets or to genres such as gaming, education, or news commentary.

Additionally, this study only examined channels with at least one sponsored video. Therefore, the impact of sponsorships on channels that haven't yet published sponsored content remains unknown. When discussing creators without sponsored content, this limitation should be carefully considered when referencing this study.

Another important constraint involves the exclusion of binary sentiment-based modelling. Although a binary variable, has_positive_comment, was initially constructed. A logistic model with this outcome could have served as a robustness check, especially for sentiment polarity. Future work may benefit from including this dimension and validating it against viewer survey data or comment-level embeddings.

In summary, while the current design prioritised interpretability and within-subject control, future research can extend these foundations with richer data sources, broader sampling, and alternative modelling frameworks. Such extensions would offer deeper insight into the shifting norms of influencer-brand dynamics in digital media.

6 Conclusion

Influencer marketing is growing exponentially, with increasing sponsorships in various creator collaborations. In this study, how sponsorships impact the YouTube creators' credibility and their audiences' engagement has been thoroughly discussed by analysing a dataset with 18,937 videos across 137 channels based in the U.S..

This study has successfully closed several gaps identified in the existing literature (Literature Review § 2.5): Firstly, by employing a fixed-effects regression framework (Methodology § 3.2.2), this study directly compared sponsored versus organic content within the same YouTube channel, isolating the sponsorship effect from between-creator heterogeneity for clearer results and analysis (Table 5). Secondly, rather than relying on a single indicator, four engagement metrics: views, likes, comments and positive-comment ratio, were examined and it was demonstrated that while quantity metrics remain unchanged by sponsorship, quality (sentiment) improves significantly (Analysis § 4.3.2, Table 6). Thirdly, this study incorporates visual cues, namely brightness, saturation, colour temperature, and face count, into analysis for the first time, indicating that high brightness and warmer colour tones reduce engagement on sponsored posts, whereas visible faces enhance credibility (Analysis § 4.4.3). Other than that, utilising data from June 2022 to June 2024, this study aimed to capture the "long tail" of post-COVID content, addressing the scarcity of large-scale, recent empirical studies in influencer marketing (Methodology § 3.1.2). In addition, channel size was introduced as a moderator and found that smaller channels exhibit more positive engagement when sponsored, suggesting niche audiences are more tolerant of commercial messaging (Analysis § 4.4.2, Table 7). Methodologically, the combined use of Source Credibility and Parasocial Interaction frameworks in a YouTube sponsorship context, and a suite of robustness checks (IQR-based outlier filtering, leave-one-out, balanced-panel) reinforces confidence in findings. Practical contributions extend to clear guidance for both brands and creators on optimising sponsored content without harming audience trust.

The results show that sponsored videos do not significantly alter view, like or comment counts within a channel, but they do shift the proportion of positive comments ($\beta = +0.076$, $p < 0.05$)(Analysis § 4.3.2, Table 5). Therefore, emphasis should be placed on sentiment management, for instance, crafting calls-to-action that invite supportive feedback and build the sense of community. It is noticeable that micro channels experienced a more positive engagement lift when sponsoring ($p < 0.01$). Brands targeting niche audiences can be confident that sponsorships will not backfire, provided that visual authenticity is maintained (Analsis § 4.4.2, Table 7). Moreover, thumbnail features moderate sponsorship effects. Avoid overly bright or warm-toned thumbnails for sponsored posts, but feel free to retain the usual title and description structure because these had no detectable impact on engagement in sponsored contexts (Analysis § 4.4.3). In summary, the results underscore that sponsorship need not compromise engagement or credibility, so long as creators attend to visual design, transparent labelling and audience relationship maintenance.

However, several limitations exist, reliance on keyword and description-based tagging (Methodology § 3.1.5) may misclassify subtle or unlabelled sponsorships. Future work should integrate NLP and computer-vision methods to improve labelling accuracy. Also, only the first 50 most-liked comments were extracted per video (Methodology § 3.1.2) and the engagement metrics are limited, which may fail to capture comprehensive patterns. Expanding to full comment streams and even backend data will significantly enhance the strength and accuracy of the analysis. Other than that, VADER's rule-based approach struggles with irony and neutral tones (Methodology § 3.1.5). Future studies could employ transformer-based models for finer-grained emotion detection. Lastly, despite fixed-effects controls, our observational design cannot definitively establish causality between sponsorship and engagement. Event-study or randomised field experiments (e.g. A/B tests of thumbnail design or disclosure language) would strengthen causal claims.

In terms of practical implications for brands, choose creators whose audience size aligns with campaign goals. For conversion (Click-throughs, Sign-ups, Purchases), partner with micro-influencers as they deliver the strongest uplift in positive engagement for sponsored content (Analysis § 4.4.2, Table 7), indicating that their audiences are more receptive and likely to act. For Brand Awareness (Reach, Impressions), partnering with mega-influencers, since mega channels guarantee scale and broad visibility while quantity metrics (views, likes, comments) remain neutral for sponsorships across all sizes (Analysis § 4.3.2, Table 5). In terms of the implications for creators, optimising thumbnails for moderate brightness and neutral-warm tones, and maintaining visible human elements in sponsored content is crucial. The most important thing is to build the sense of community while growing. Foster community by promptly replying to comments, disclosing relationships with brands, running Q&A sessions or hosting offline/online events. These actions strengthen parasocial bonds and buffer against any perceived loss of authenticity (Discussion § 5.1). By addressing these limitations, both scholars and practitioners can more precisely understand and ethically leverage the dynamics of sponsorship on YouTube, unfolding the patterns of influencer marketing in more depth.

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8 APPENDIX

Appendix A: Dataset Structure

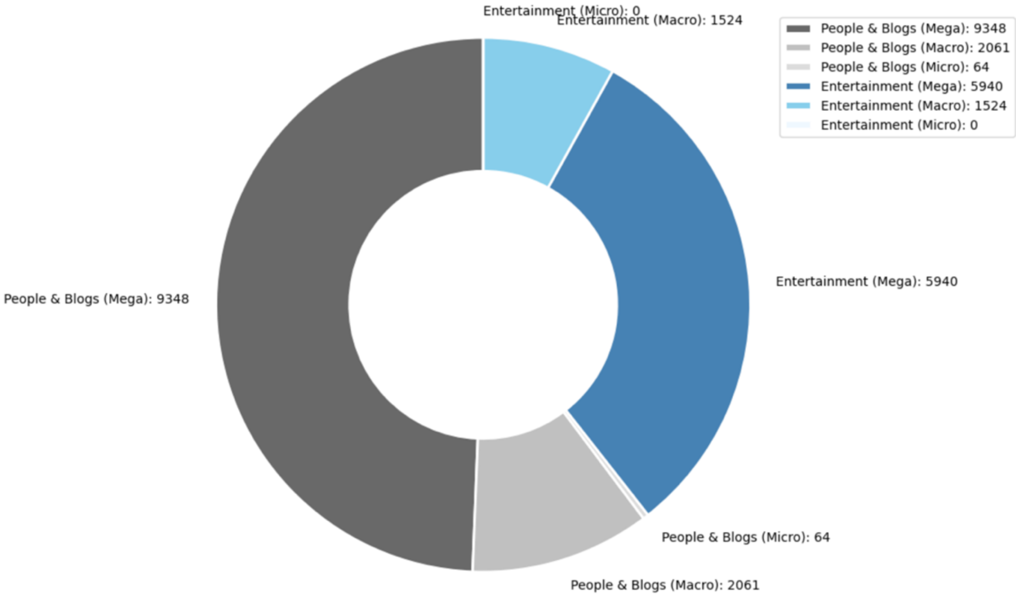

Figure 13: Video Distribution by Category and Channel Size

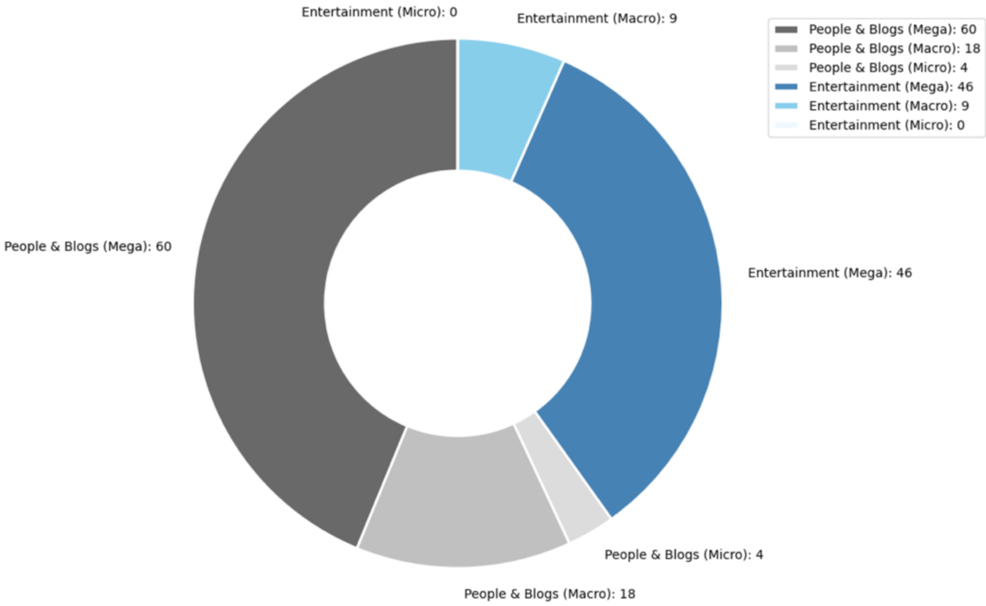

Figure 14: Channel Distribution by Category and Channel Size

Variable	count
Channel Count	137.00
mean	138.23
std	133.40
min	7.00

25%	40.00
50%	91.00
75%	200.00
max	573.00

Table 8: Statistical Summary of the Number of Videos per Channel

Appendix B: Distribution of Sponsorship

	sponsored video per channel	sponsor percentage (%)
mean	19.81	15.88
std	52.32	24.58
min	1.00	0.20
25%	1.00	1.84
50%	4.00	5.00
75%	8.00	16.44
max	387.00	98.22

Table 9: Statistical Summary of the Sponsored Video and Sponsored Percentage per Channel

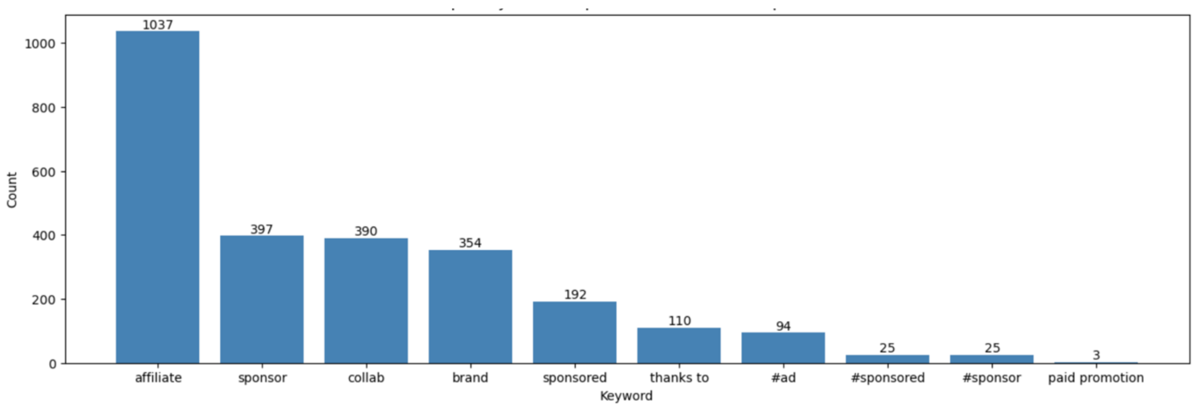

Figure 15: Top 10 Keywords in Sponsored Content Descriptions

Appendix C: Engagement Metrics: Overall Summary

	view_count	like_count	comment_count
mean	5858241.59	157809.38	2773.39
std	25321239.97	748769.06	10832.93
min	50.00	3.00	1.00
25%	35065.00	1122.00	48.00
50%	364448.00	10104.00	327.00

75%	2653684.00	70278.00	1700.00
max	703744431.00	29782915.00	288000.00

Table 10: Engagement Metrics Summary

	Average view_count	Average like_count	Average comment_count
organic	6505620.53	174849.83	2984.67
sponsored	1988518.45	55940.66	1510.43

Table 11: Average Engagement by Sponsorship

Appendix D: Visual Inspection of Distributions

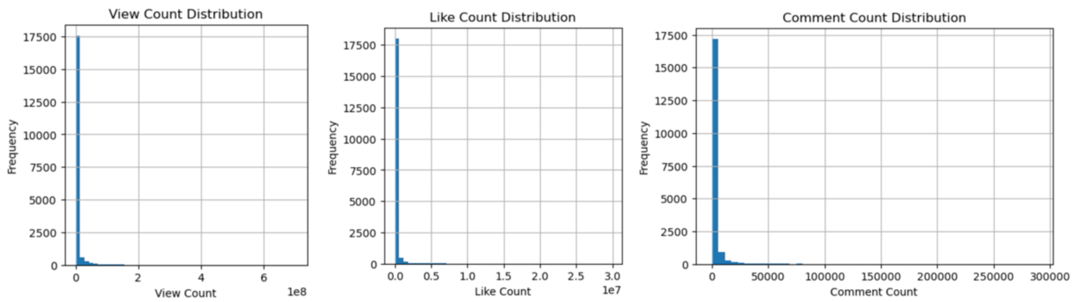

Figure 16: Engagement Metrics Distribution Before Log-Transformation

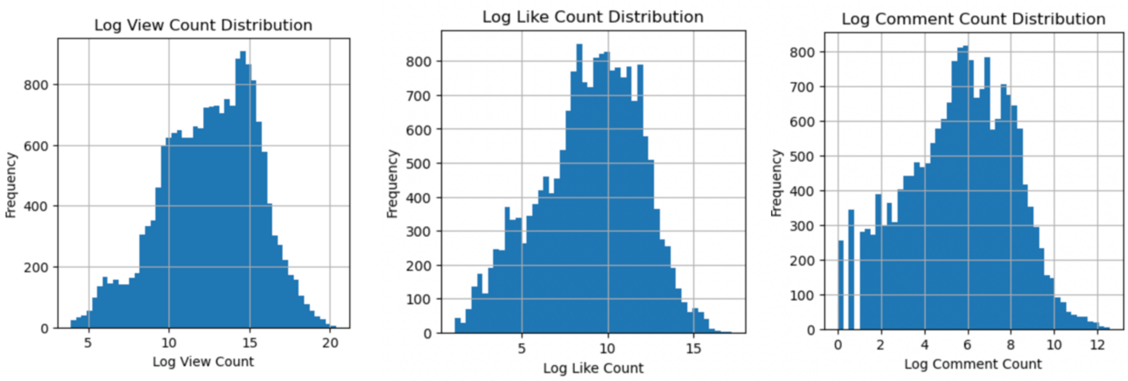

Figure 17: Engagement Metrics Distribution After Log-Transformation

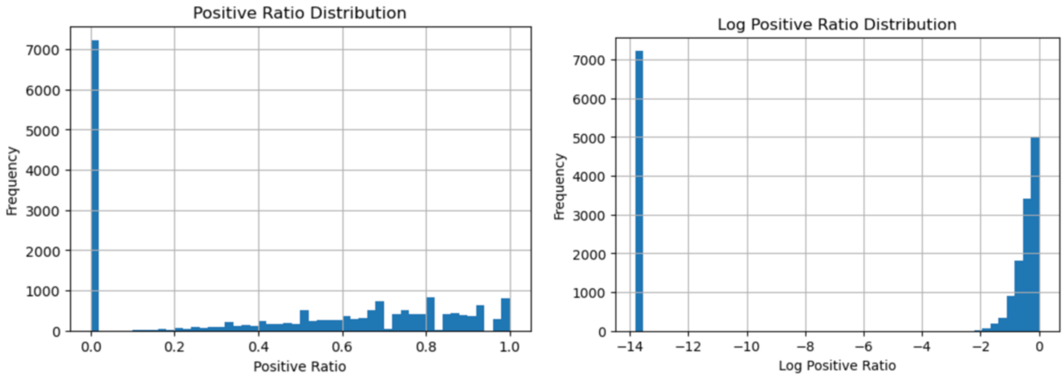

Figure 18: Positive Comment Ratio Before/ After Log-Transformation with a Small Constant

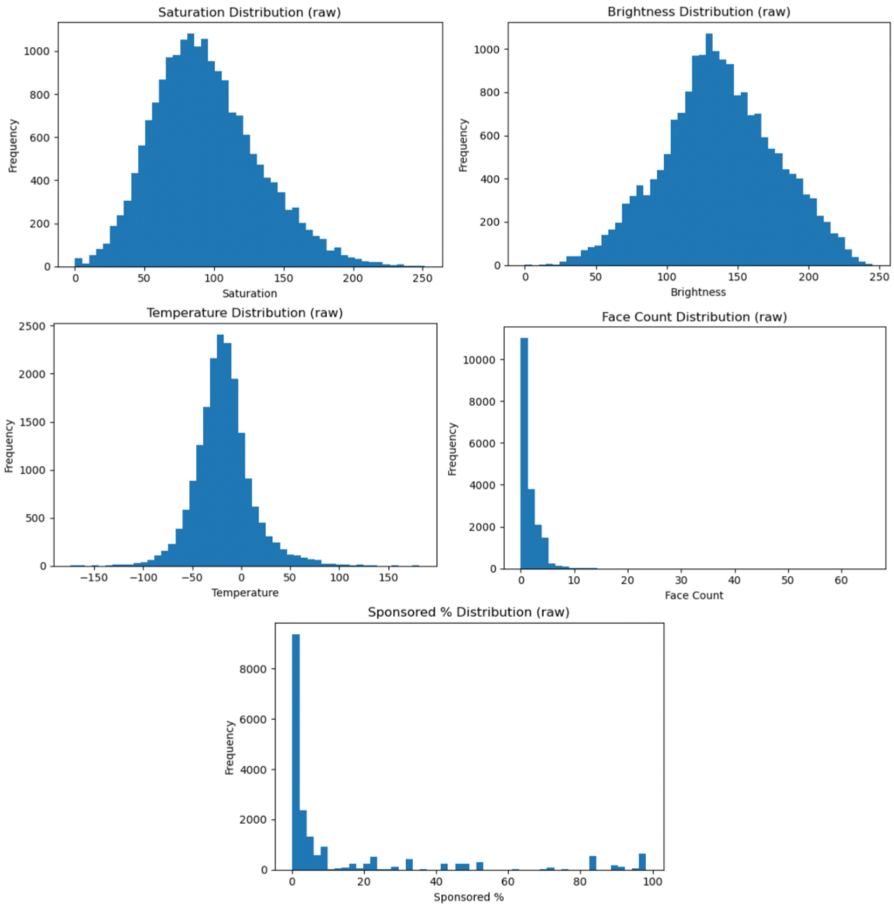

Figure 19: Distribution of Other Variables

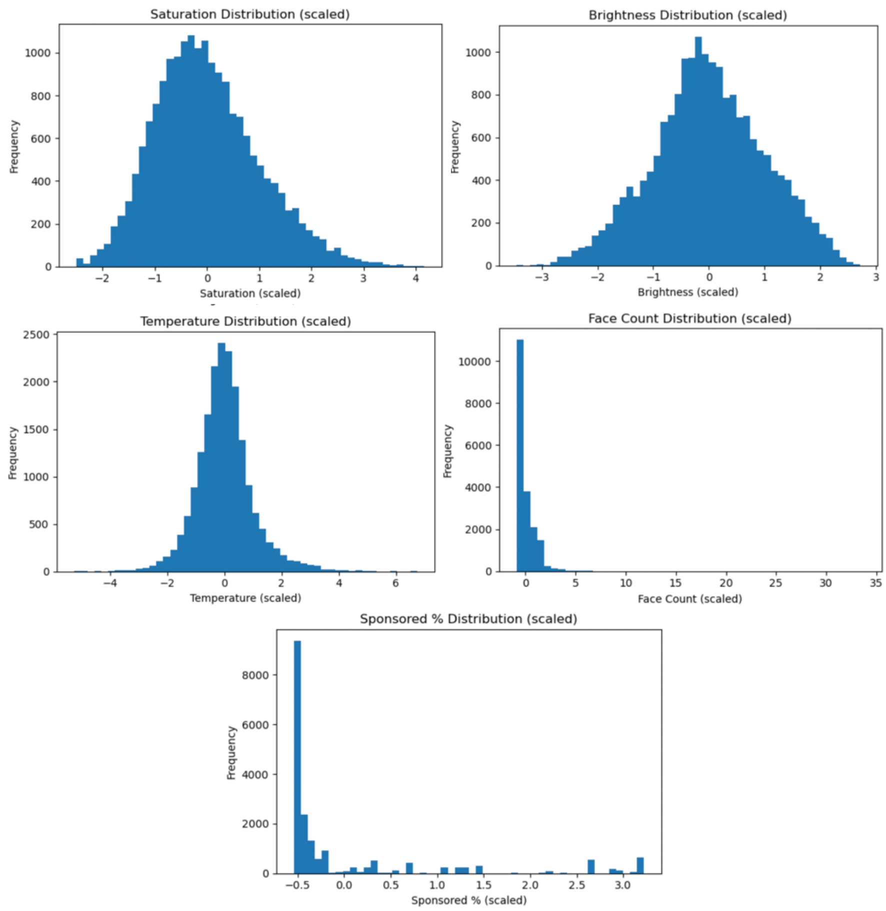

Figure 20: Distribution of Other Variables after Scaled

Appendix E: RQ3: Channel-Level Moderators

Engagement Metric: log_view_count			
MODERATOR	**TERM**	**COEFF**	**P-VALUE**
size x sponsored_content_pct	is_sponsored	0.020486	0.896459
size x sponsored_content_pct	is_sponsored:size[T.mega]	-0.197429	0.467408
size x sponsored_content_pct	is_sponsored:size[T.micro]	-0.059562	0.899386
size x sponsored_content_pct	is_sponsored: sponsored_content_pct	-0.002548	0.350961
size x sponsored_content_pct	is_sponsored:size[T.mega]: sponsored_content_pct	0.007233	0.104589
size x sponsored_content_pct	is_sponsored:size[T.micro]: sponsored_content_pct	0.021291	0.004007
Engagement Metric: log_like_count			
MODERATOR	**TERM**	**COEFF**	**P-VALUE**
size x sponsored_content_pct	is_sponsored	-0.026183	0.867181

size x sponsored_content_pct	is_sponsored:size[T.mega]	-0.352394	0.245447
size x sponsored_content_pct	is_sponsored:size[T.micro]	-0.973665	0.240147
size x sponsored_content_pct	is_sponsored: sponsored_content_pct	-0.002056	0.464488
size x sponsored_content_pct	is_sponsored:size[T.mega]: sponsored_content_pct	0.005885	0.233462
size x sponsored_content_pct	is_sponsored:size[T.micro]: sponsored_content_pct	0.025856	0.059237

Engagement Metric: log_comment_count

MODERATOR	TERM	COEFF	P-VALUE
size x sponsored_content_pct	is_sponsored	-0.135739	0.415420
size x sponsored_content_pct	is_sponsored:size[T.mega]	0.219909	0.420702
size x sponsored_content_pct	is_sponsored:size[T.micro]	0.201805	0.484434
size x sponsored_content_pct	is_sponsored: sponsored_content_pct	0.002968	0.290986
size x sponsored_content_pct	is_sponsored:size[T.mega]: sponsored_content_pct	0.002557	0.582047
size x sponsored_content_pct	is_sponsored:size[T.micro]: sponsored_content_pct	0.014781	0.002035

Engagement Metric: log_positive_ratio_eps

MODERATOR	TERM	COEFF	P-VALUE
size x sponsored_content_pct	is_sponsored	-0.002276	0.991478
size x sponsored_content_pct	is_sponsored:size[T.mega]	0.140693	0.527675
size x sponsored_content_pct	is_sponsored:size[T.micro]	0.002276	0.991478
size x sponsored_content_pct	is_sponsored: sponsored_content_pct	0.002011	0.512101
size x sponsored_content_pct	is_sponsored:size[T.mega]: sponsored_content_pct	-0.004423	0.194049
size x sponsored_content_pct	is_sponsored:size[T.micro]: sponsored_content_pct	-0.002011	0.512101

Appendix F: RQ3: Content-Level Moderators

Engagement Metric: log_view_count			
MODERATOR	**TERM**	**COEFF**	**P-VALUE**
brightness_scaled	is_sponsored	-0.049887	0.702292
brightness_scaled	is_sponsored: brightness_scaled	0.030177	0.582716
saturation_scaled	is_sponsored	-0.052051	0.717160
saturation_scaled	is_sponsored: saturation_scaled	-0.004612	0.922166
temperature_scaled	is_sponsored	-0.061288	0.664235
temperature_scaled	is_sponsored: temperature_scaled	-0.069382	0.032202
face_count_scaled	is_sponsored	-0.063225	0.658906
face_count_scaled	is_sponsored: face_count_scaled	0.053174	0.379901
title_word_count	is_sponsored	-0.273279	0.382595
title_word_count	is_sponsored: title_word_count	0.024280	0.282162
title_upper_letters	is_sponsored	-0.120959	0.534228
title_upper_letters	is_sponsored: title_upper_letters	0.005696	0.362198
description_word_count	is_sponsored	-0.139249	0.578089
description_word_count	is_sponsored: description_word_count	-0.000014	0.987428
Engagement Metric: log_like_count			
MODERATOR	**TERM**	**COEFF**	**P-VALUE**
brightness_scaled	is_sponsored	-0.201762	0.164143
brightness_scaled	is_sponsored: brightness_scaled	0.083964	0.182402
saturation_scaled	is_sponsored	-0.235418	0.151783
saturation_scaled	is_sponsored: saturation_scaled	-0.006569	0.900848
temperature_scaled	is_sponsored	-0.246590	0.130788
temperature_scaled	is_sponsored: temperature_scaled	-0.067728	0.020730
face_count_scaled	is_sponsored	-0.240979	0.147584
face_count_scaled	is_sponsored: face_count_scaled	0.048355	0.412512
title_word_count	is_sponsored	-0.549693	0.129252
title_word_count	is_sponsored: title_word_count	0.034797	0.199323
title_upper_letters	is_sponsored	-0.268230	0.202180

title_upper_letters	is_sponsored: title_upper_letters	0.003816	0.548769
description_word_count	is_sponsored	-0.322435	0.270371
description_word_count	is_sponsored: description_word_count	0.000405	0.684531

Engagement Metric: log_comment_count

MODERATOR	TERM	COEFF	P-VALUE
brightness_scaled	is_sponsored	0.140197	0.347367
brightness_scaled	is_sponsored: brightness_scaled	-0.008842	0.891866
saturation_scaled	is_sponsored	0.186810	0.254714
saturation_scaled	is_sponsored: saturation_scaled	-0.019345	0.720185
temperature_scaled	is_sponsored	0.181473	0.257974
temperature_scaled	is_sponsored: temperature_scaled	-0.034039	0.359867
face_count_scaled	is_sponsored	0.176264	0.278028
face_count_scaled	is_sponsored: face_count_scaled	0.008624	0.869866
title_word_count	is_sponsored	0.094727	0.779569
title_word_count	is_sponsored: title_word_count	0.010262	0.661906
title_upper_letters	is_sponsored	0.153705	0.480874
title_upper_letters	is_sponsored: title_upper_letters	0.001541	0.844194
description_word_count	is_sponsored	0.085943	0.737039
description_word_count	is_sponsored: description_word_count	-0.000340	0.746312

Engagement Metric: log_positive_ratio_eps

MODERATOR	TERM	COEFF	P-VALUE
brightness_scaled	is_sponsored	0.075402	0.025311
brightness_scaled	is_sponsored: brightness_scaled	-0.057064	0.048939
saturation_scaled	is_sponsored	0.076115	0.050205
saturation_scaled	is_sponsored: saturation_scaled	-0.016211	0.772489
temperature_scaled	is_sponsored	0.077960	0.062706
temperature_scaled	is_sponsored: temperature_scaled	0.015264	0.789315
face_count_scaled	is_sponsored	0.071899	0.059180
face_count_scaled	is_sponsored: face_count_scaled	-0.036415	0.371424
title_word_count	is_sponsored	0.396964	0.174899
title_word_count	is_sponsored:	-0.037224	0.244699

	title_word_count		
title_upper_letters	is_sponsored	0.088701	0.134107
title_upper_letters	is_sponsored: title_upper_letters	-0.001719	0.636019
description_word_count	is_sponsored	0.063354	0.293933
description_word_count	is_sponsored: description_word_count	-0.000054	0.842319

Appendix G: Visual Cues as Contextual Amplifiers

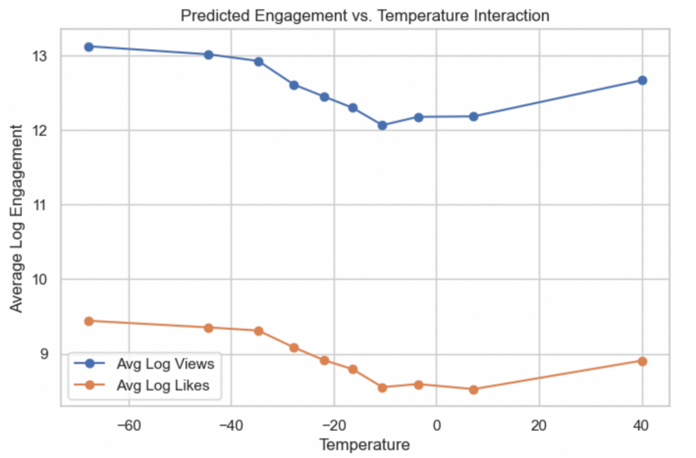

Figure 21: Predicted Engagement vs. Temperature Interaction