

From Sentiment to Search Volume: Impact Assessment of Video Branding Campaign

Gangmin Li

Xi'an Jiaotong-Liverpool University, China

Gangmin.li@xjtlu.edu.cn

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Abstract: In the growing reliance on social media for brand campaigns, this study aims to identify efficient and reliable methodologies for evaluating their success. Using a quantitative approach, we investigated two key metrics: sentiment analysis (via VADER) and Brand Search Volume (BSV) via Google Trends. We employed an OLS regression model to examine how sentiment scores and negative-to-positive comment ratios influence BSV. The findings reveal strong positive correlations between sentiment scores, total comment counts, and BSV changes in the subsequent month (28.3% increase per sentiment score unit) and year (6.57% increase). Higher negative-to-positive comment ratios were significantly associated with BSV declines, with negative sentiments showing persistent short- and long-term impacts. The study highlights the need to integrate emotional response metrics (e.g., sentiment analysis) with behavioural indicators (e.g., BSV) to assess campaigns' effects on consumer attitudes and behaviour. It emphasises that managers and policymakers must ensure campaigns secure initial positive reception and maintain long-term relevance.

Keywords: Brand search volume; OLS regression; Sentiment analysis; Social media evaluation; Video branding campaigns

1. Introduction

In digital marketing, one prominent strategy entails implementing video campaigns to promote or enhance brand building. Many business organisations leverage widely accessible digital platforms such as YouTube and TikTok to promote their brands. However, the increasing use of social media for brand campaigns does not always translate to expected branding outcomes. A typical example is the 2019 Gillette brand campaign¹, which generated 27 million views on YouTube. The controversy surrounding its "We Believe" advertisement is the opposing perceptions among its viewers. The critics believe it is a "virtue signalling" and alienating its customer base by reprimanding male behaviour, which resulted in particularly negative customer sentiment². YouTube data showed 63% negative sentiment and a negative-to-positive comment ratio of 45% to 34%. Consequently, Gillette's net favourability declined by 10 points to 58%, though it rebounded to 64% a year later. This example illustrates how a hard built brand can be easily lost [1]. It also shows that customer perceptions of a brand can be influenced by online opinions, which will further impact on customers' behaviour to response to the video campaign [2]. This behaviour is measured by a widely accepted metric for branding campaigns, the brand search volume (BSV) [3-4].

Despite the assumption that initial campaign sentiment drives brand discourse, awareness, and BSV, few studies have examined the relationship between sentiment and BSV [5-6]. Furthermore, there is a lack of clarity on whether and how positive or negative customer sentiments toward brand campaigns impact BSV over time. While positively received campaigns may increase search volume, it remains unclear

¹ McCluskey, Megan. "Gillette Makes Waves with Controversial New Commercial". Time, 15 Jan. 2019, Available: www.time.com/5503156/gilletterazors-toxic-masculinity/.

² A Case Study on Gillette: "The Best Men Can Be" Campaign. The Brand Hopper, Available: <https://thebrandhopper.com/2024/02/06/a-case-study-on-gillette-the-best-men-can-be-campaign/>.

whether campaigns with negative sentiment also sustain high BSV or incur negative impacts [2, 5]. This gap is critical for marketers, informing whether to leverage controversy for awareness or prioritise enhancing positive sentiment. Evaluating video campaigns is challenging due to latency in impact manifestation and the complexity of isolating causal factors [6].

This paper addresses this gap by analysing early audience sentiment toward brand video campaigns and tracking subsequent BSV fluctuations on Google Trends. By evaluating these metrics and their correlation, we aim to identify a precise method for assessing video campaign impact.

2. Related works

Arguments about the objective of a brand campaign led to different evaluation methods. Sentiment analysis is the most adopted initial assessment indicator, followed by the measurements of the increasing customer interests and, ultimately, the turnover and customer purchases.

2.1. Sentiment Analysis as an Early Indicator

Rietveld *et al.* [7] and Sabate *et al.* [8] have shown that public reactions on social media can signal potential brand success or failure. Both studies emphasise that emotional responses reflected in online interactions like comments, likes, shares, etc., can forecast trends in consumer interest, buying intentions, and brand loyalty. Poels and Dewitte [9] found that consumers' positive and negative sentiments correlate with memory recall and brand attitude, highlighting sentiment analysis as a key method for evaluating campaign effectiveness. Many studies have used sentiment analysis to assess branding campaign success [10-12]. Rietveld *et al.* [7] even used it to predict the long-term performance of YouTube video brandings. However, these studies also revealed limitations associated with sentiment analysis. It can only categorise users' online text about brand campaigns into predefined exclusive categories (e.g., positive, negative, neutral) by calculating a compound score based on word valence, normalising it between -1 and 1 with set thresholds. This calculation has fundamental issues of inability to understand sarcasm, irony, and other complex forms of humour frequently found in text. Additionally, it fails to measure how sentiment impacts users' behavioural changes, the core values of many branding campaigns that aim to drive customer engagement and potential turnover.

Many other researchers have worked on separating positive and negative sentiments to study the impact of a brand campaign. Intuitively, we want a branding campaign has a positive impact on customers and avoid the negative sentiment [1]. So, the positive and negative sentiment ratio could be a credit metric to evaluate the success of the brand campaign.

Some researchers argued that the negative sentiment may impact brand engagement and boost awareness as much as the positive sentiment, if not more. Berger *et al.* [13] claim that negative publicity can sometimes boost consumer interest, especially for lesser-known brands. They argued that negative coverage could raise brand awareness, and controversy or criticism may be a catalyst to interest, leading consumers to seek more information on the brand and potentially leading to increased audience engagement or sales driven by curiosity. Such "any publicity is good publicity" occurs because short-term bursts of attention can be linked to controversy, despite long-term outcomes being more negative. Malthouse *et al.* [14] argued that extremely engaging or viral videos, regardless of sentiment, can still generate significant brand exposure. For example, a polarising video may get many negative comments but remain at millions of views and drive much online conversation. In these cases, virality and controversy may create exposure, even as sentiment measures are negative.

Rozin and Royzman [15] are alarmed that in digital advertising, unfavourable reactions to a brand or campaign are likely to have more profound consequences than positive feedback, especially when these reactions are publicly visible and widely shared. Most research will devalue the campaign's success if its negative sentiment is high.

Research by Darke, Ashworth, and Ritchie [16] found that even brief exposure to negative information about a brand can lead to persistent changes in attitude, even if the information is later refuted. They argue that consumers are often influenced not only by their direct interactions with a brand but also by the sentiments shared by others, especially those within their digital social circles. This effect is amplified in platforms like YouTube, where comment sections act as a form of real-time peer review and collective

opinion formation. Holbrook and Batra [17] also stress that consumers rely more heavily on affective responses than rational evaluations when making brand-related decisions. Therefore, an ad that provokes negative emotions, such as anger, disappointment, or offence, can result in brand aversion or disengagement. Berger, Sorensen, and Rasmussen [13] examined the relationship between negative sentiment and the user's interest in the brand. They discovered that although harmful exposure may boost awareness, particularly for small brands, it will generally cause irreparable reputational damage to larger ones.

2.2. Brand Search Volume as a Metric of Increasing Interests

Although sentiment analysis is valuable for measuring consumer emotional response immediately after a brand campaign, the divergence and disagreement on the positive and negative emotions make it hard to assess the conclusive success of a brand campaign. Many researchers argue that sentiment analysis results must be contextualised with other measures such as engagement and visibility [17-18]. Together, they can build a complete picture of how a campaign is performing and prevent the danger of making judgments based only on emotional tone. Brand search volume (BSV), typically measured with metrics like Google Trends, has increasingly served as a proxy to gauge consumer interest, brand awareness, and campaign effectiveness [19]. More and more researchers have used search volume data to quantify campaign performance. Da *et al.* [19] introduced the Search Volume Index (SVI) to predict market-level behaviour. When consumers engage with advertising and branded content, it is logical that they would seek more information, often via search engines, if they are interested. Thus, search activity fluctuations can indicate public interest and sentiment toward a brand.

Google Trends provides normalised, aggregated data on how often specific search terms are entered compared to overall search volume across different regions and periods. Choi and Varian demonstrated that Google Trends can predict all kinds of economic behaviour, from product demand to travel bookings and even stock market trading activity [18]. It is a convenient and almost real-time way of keeping tabs on attention to brands, products, or campaigns.

2.3. Other Complementary Metrics

While sentiment expresses what people think about a brand, brand search behaviour shows whether or not they care enough or are intrigued enough to look further. Researchers also use other measures such as views, comments, like-to-dislike ratio, and peak engagement timing to reflect engagement and visibility, which are the legitimate goals of the brand campaigns. For example, Malthouse *et al.* [14] used the number of views online for a YouTube video branding to assess the campaign's exposure. Many views may indicate that a campaign resonated with viewers, even if the sentiment is negative. On the other hand, a video with few views may suggest limited users' interest or relevance. Similarly, the likes-to-dislikes ratio provides a general indication of audience approval. Rietveld *et al.* [7] studied the timing factor of a brand campaign. Their research has shown that the first few days after a campaign is released are critical for determining how people perceive it. Early feedback will tend to inform all further interaction. It can shape how algorithms used by platforms and other recommendation software create views of the video [7] since a lot of marketing platforms use software bots and agents to gather opinions of a new campaign. A first spike of negative feedback will result in lower exposure through search queries and recommendation algorithms. At the same time, early positive responses will increase views and engagement by automatic recommendation algorithms. These automatic algorithms and recommendation engines can also amplify the impact of the initial sentiment of users on a large scale—more studies on the correlation between sentiment and metrics such as search volume are needed. Otherwise, researchers may erroneously attribute fluctuations in consumer interest to sentiment alone, ignoring underlying dynamics like virality, influencer amplification, or media coverage.

BSV is regarded as a behavioural metric that can be balanced with emotional and cognitive measures such as sentiment analysis. While sentiment expresses what people think about a brand, search behaviour shows whether or not they care enough or are intrigued enough to look further. Combining the sentiment analysis-based emotional tone and the search trend-based behavioural data is more effective in presenting the big picture of campaign reach.

3. Research Methodology

Our research objectives are identifying reliable and accurate methods for evaluating brand campaign performance and examining the relationship between the online sentiments and subsequent BSV. The central hypothesis in the research is that negative sentiment in the brand campaigns in the first few days after release will lead to a decrease in BSV for the brand. Therefore, it will mark the brand's unsatisfactory campaign. Our research adopts the "positivist research paradigm". Positivism relies on the "hypothetic deductive method to verify a priori hypotheses, where functional relationships can be derived between causal and explanatory factors and outcomes" [20]. Therefore, our first goal is to assess the initial sentiment after the brand campaign is released. Then, looking into the BSV. We leverage YouTube video campaigns and comments posted on YouTube to conduct sentiment analysis and search volume on Google to assess further the change in customer interest shifting. A further study of the correlation between the two metrics is taken to ensure the two metrics are complementary, not repetitive or contradictory, to form a method overall for assessing the success of a video branding campaign.

3.1. The Data and The Model for Sentiment Analyses

Our study uses brand campaign data from 2022 to 2024 on YouTube, with the following inclusion/exclusion criteria:

- The brand campaign is posted on the brand's official YouTube channel, not elsewhere.
- The video has garnered more than 500,000 views in total.
- The brand must be relatively well-established before the campaign to ensure high growth is not skewed by new or unicorn start-ups gaining traction.

A total of 17 brand campaigns' YouTube comments were selected for sentiment analysis. Only the first comment (excluding replies) was analysed to mitigate potential complications in chat threads or conversations, where the original comment's overall sentiment might be diluted. YouTube comments from the first five days were collected after the campaign launched. The comments were processed, cleaned, and analysed to create a sentiment distribution for each campaign, with a continuous sentiment score alongside the ratio of negative to positive comments, reflecting the overall emotional tone of audience reactions. We also obtained the following data for each brand campaign: Like to Dislike Ratio, Total number of views, Total number of comments and Video length in minutes.

For the sentiment analysis model, we used VADER primarily because of its capacity to parse YouTube comments effectively, considering the various slang and informal texts as prevalent within the informal YouTube comment section. VADER has been optimised to capture the nuances within the informal comments by parsing the emotional tone without requiring extensive training on the comments, as it has been pre-programmed to handle such emotional and informal intricacies. VADER was also used to capture the overall positive and negative comment ratio. The threshold for positive and negative sentiments was set at the typical value of 0.05. That is the compound score of a comment greater than 0.05 for positive sentiment, less than -0.05 for negative sentiment and any value in between for neutral sentiment. Table 1 presents the five-number summary of the compound sentiment score for the 17 brand campaigns.

Table 1. The statistical results of the sentiment data from the YouTube API for the 17 brand campaigns

	Mean	Median	Standard deviation	Minimum	Maximum
Sentiment Score	0.00176	0.05	0.225	-0.35	0.35
Neg/Pos Comment Ratio	0.799	0.65	0.482	0.2	1.75
Total Comments (1000)	9.63	9.2	3	5.4	15
Total Views (Million)	2.74	2.5	1.05	1.3	5
Like/Dislike Ratio	7.09	7.2	3.53	2.1	13.5

As seen from Table one, first of all, the statistics of the total comments with a mean of 9.63 thousand and a standard deviation of 3 thousand show a relatively large fluctuation in the number of comments for different video campaigns. This implies that the popularity and engagement levels of the brand campaigns vary significantly, as some may attract a much larger number of comments while others receive far fewer. The mean and the median are pretty close to each other, indicating that the distribution of total views for the brand campaigns is relatively uniform, suggesting a certain consistency in the audience reach to some extent. The significant standard deviation of 3.53 of the like/dislike ratio shows a considerable variation in

the like/dislike ratios among different brand campaigns. This implies that the audience's reactions and preferences towards the content of these campaigns are pretty diverse, with some campaigns receiving a much higher ratio of likes to dislikes than others. The most important information we can get is the sentiment score. It has a mean of 0.00176, highlighting the balanced distribution of positive and negative sentiment scores. However, the mean ratio between the negative and positive comments is less than 1, suggesting that the brand campaigns contained more negative comments than the positive ones when comparing the comments considered for the study.

3.2. The Data and The Model for Brand Search Volume

The second metric for evaluating video branding campaign success is Brand Search Volume (BSV), collected from Google Trends. For each analysed brand, weekly search volume indices were gathered over 12 weeks: six weeks before and six weeks after the campaign. This allowed us to establish a baseline for search activity to evaluate post-campaign changes. BSVs collected from Google Trends are normalised relative index from 0 to 100. To ensure consistency in values from the search engine, BSV was taken using only the brand name. The study takes two values. The changes in BSV are within the month after the campaign and the year after the campaign. We used the month-over-month change (MoM) and year-over-year change (YoY) in the search volumes as the exact metrics, where the MoM change in BSV examines the short-term impact of the brand campaign, and the YoY change in BSV examines the potential long-term consequences.

The MoM change is calculated as,

$$MoM = \frac{(BSV \text{ 1 month post_campaign}) - (baseline \text{ BSV})}{baseline \text{ BSV}} \quad (1)$$

BSV is the brand search volume, BSV 1 month post campaign is the brand search volume a month after the campaign launch, and baseline BSV is the brand search volume one day before the campaign. Therefore, by taking the baseline BSV a day before the campaign, the overall short-term impact of a brand campaign in a month can be calculated through the MoM change in brand search volume. Similarly, the YoY change is calculated as,

$$YoY = \frac{(BSV \text{ 1 year post_campaign}) - (baseline \text{ BSV})}{baseline \text{ BSV}} \quad (2)$$

The baseline BSV is the same as the MoM change in BSV, and BSV 1 year post campaign is the BSV a year after the launch of the brand campaign. This should highlight the long-term impact of the brand campaign, although there remains a potential increase in confounding factors and the potential impact of other online discourse on the Brand Search Volume. Nonetheless, this confounding factor can be somewhat mitigated with many data points.

To eliminate the brand intrinsic trend on search volume, the up-down trend in the search volume has nothing to do with the branding campaign. We have also introduced other measurements, such as MoM Growth and YoY Growth. A MoM pre-campaign search volume growth is calculated as,

$$MoM \text{ Growth} = \frac{(BSV \text{ 1 day pre_campaign}) - (baseline \text{ BSV})}{baseline \text{ BSV}} \quad (3)$$

where baseline BSV is the BSV a month before the campaign launch. The same concept applies to YoY Growth, with the baseline BSV being the BSV a year before the campaign launch, as shown in Formula 4.

$$YoY \text{ Growth} = \frac{(BSV \text{ 1 day pre_campaign}) - (baseline \text{ BSV})}{baseline \text{ BSV}} \quad (4)$$

Table 2 shows the five-number summary of the data we have taken and calculated from Google Trends.

Table 2. The statistical results of the BSV from the Google Trends API for the 17 brand campaigns

	Mean	Median	Standard deviation	Minimum	Maximum
Previous MoM Growth	0.0235	0.03	0.0285	-0.05	0.06
Previous YoY Growth	0.00647	0.01	0.00996	-0.02	0.02
Video Length (min)	2.49	2.5	0.42	1.8	3.1
Search Volume Change (MoM)	-0.0112	0.01	0.061	-0.11	0.07
Search Volume Change (YoY)	-0.00294	0	0.0145	-0.03	0.02

Table 2 shows the relatively concentrated video lengths among the campaign videos due to the close mean and median and the slight standard deviation of 0.42. The video lengths fluctuate around the mean

value, all within 1.8 minutes to 3.1 minutes. Previous MoM and YoY Growth mean shows that the previous MoM growth rate is relatively larger than the YoY growth rate. The larger standard deviation of the previous MoM growth indicates more significant fluctuation in the MoM growth rates across different periods, with greater variability than the YoY growth rates. Perhaps the most interesting finding is the unfavourable trends in search volume changes after the video campaign. This is indicated by the negative mean of the MoM at -0.0112 and the YoY at -0.00294. In particular, the standard deviation of the search volume change (MoM) is 0.061, which is relatively large, suggesting significant differences in the MoM search volume changes across different periods.

3.3. The Model and Variables for Correlation Analyses

We used the Ordinary Least Squares (OLS) model for regression and Pearson's correlation coefficient to select independent variables by examining the strength and direction of the relationship between dependent and independent variables. Multicollinearity analyses were conducted to exclude highly correlated variables before specifying the OLS model.

3.3.1. Independent Variable Selection with Pearson's R

Table 3 shows the matrix of Pearson's correlation coefficient, also called Pearson's R, of variables. It is used to examine the strength and direction of the relationship between the different variables.

Table 3. The Pearson's correlation matrix for the dependent and independent variables

		Sentiment Score (Avg.)	Neg/Pos Ratio	Total Comm	Total Views (M)	Like/Dislike Ratio	SVC (MoM%)	SVC (YoY %)	Pre MoM Growth (%)	Pre YoY Growth (%)
Sentiment Score	r	—								
	p	—								
Neg/Pos Comment Ratio	r	-0.975	—							
	p	<.001	—							
Total Comments	r	-0.064	-0.097	—						
	p	0.807	0.712	—						
Total Views (M)	r	0.221	-0.341	0.882	—					
	p	0.394	0.181	<.001	—					
Like/Dislike Ratio	r	0.975	-0.945	-0.058	0.26	—				
	p	<.001	<.001	0.825	0.313	—				
Search Volume Change (MoM)	r	0.983	-0.991	0.064	0.32	0.963	—			
	p	<.001	<.001	0.806	0.211	<.001	—			
Search Volume Change (YoY)	r	0.966	-0.97	0.058	0.318	0.962	0.972	—		
	p	<.001	<.001	0.824	0.214	<.001	<.001	—		
Previous MoM Growth	r	0.83	-0.83	0.226	0.43	0.8	0.837	0.8	—	
	p	<.001	<.001	0.383	0.085	<.001	<.001	<.001	—	
Previous YoY Growth	r	0.738	-0.749	0.102	0.284	0.692	0.743	0.704	0.927	—
	p	<.001	<.001	0.697	0.269	0.002	<.001	0.002	<.001	—
Video Length (min)	r	0.359	-0.261	-0.052	0.129	0.447	0.339	0.344	0.406	0.259
	p	0.157	0.311	0.842	0.621	0.072	0.184	0.177	0.106	0.316

Pearson's correlation matrix highlights the correlations among all variables considered in the study. As can be seen, the sentiment score and Neg/Pos comment ratio have almost perfect negative correlation, highlighting their capacities to capture sentiments but in the opposite spectrum. Sentiment score also correlates highly with Like/Dislike ratio ($r=0.975$, $p<0.001$), highlighting the almost perfect positive correlation between the two variables. Therefore, sentiment scores exhibit high correlations with other independent variables, necessitating the elimination of these variables to mitigate collinearity. Sentiment score also seems to have a statistically significant, positive, and strong correlation with the dependent variables Search Volume Change (MoM) ($r = 0.983$, $p<0.001$) and Search Volume Change (YoY) ($r = 0.966$, $p<0.001$). Therefore, there seems to be a high correlation between the dependent and independent variables, suggesting the positive sentiment's potential impact on the BSV in the subsequent month and year. They all indicate that the sentiment score is the first variable needed for the regression model.

3.3.2. Independent Variables' Multicollinearity Analyses

The checking is carried out before the model can be formulated to ensure no multicollinearity among the independent variables. Table 4 shows the Collinearity Statistics between the independent variables.

Table 4. Collinearity Statistics between the variables taking MoM as a dependent variable

Statistics Item	VIF	Tolerance
Sentiment Score	167.81	0.00596
Neg/Pos Comment Ratio	113.55	0.00881
Total Comments	25.30	0.03952
Total Views (M)	11.64	0.08594
Like/Dislike Ratio	46.30	0.02160
Previous MoM Growth	40.82	0.02450
Video Length	2.34	0.42752
Previous YoY Growth	18.97	0.05272
Search Volume Change (YoY)	30.20	0.03311

From Table 4, the Variance Inflation Factor (VIF) and the Tolerance between the variables when considered as independent variables for the regression model with Search Volume Change (MoM) as the dependent variable, high VIF values (>10) and low tolerance values indicate significant multicollinearity among the variables. When variables are highly collinear, they can distort the results of a regression model and make it difficult to accurately assess the individual impact of each variable on the dependent variable. In Table 4, the only variable with a relatively low VIF (2.34) and high tolerance (0.42) is Video Length, which suggests a much weaker collinear relationship with the other variables. It is less likely to cause issues in the regression model and could potentially be retained.

3.3.3. Regression Models for MoM and YoY

After conducting correlation analyses and multicollinearity checks, four independent variables were selected via backwards elimination: previous MoM growth, video length, total comments, and sentiment score. We used two different models to predict MoM and YoY, respectively.

Model 1:

$$\text{Search Volume Change (MoM)} = \beta_0 + \beta_1 \text{SentimentScore} + \beta_2 \text{PreviousMoMGrowth} + \beta_3 \text{VideoLength} + \beta_4 \text{TotalComments} + \epsilon \quad (5)$$

And, Model 2:

$$\text{Search Volume Change (YoY)} = \beta_0 + \beta_1 \text{SentimentScore} + \beta_2 \text{PreviousYoYGrowth} + \beta_3 \text{VideoLength} + \beta_4 \text{TotalComments} + \epsilon \quad (6)$$

The results were obtained using the two regression models. Table 5 shows the results of the OLS regression model 1, and Table 6 shows the results of the OLS regression model 2.

Table 5. The OLS regression results for Model 1

Model Fit Measures				
Model	R	R ²		
1	0.991	0.983		
Model Coefficients - Search Volume Change (MoM)				
Predictor	Estimate	SE	t	P
Intercept	-0.03542	0.01749	-2.0258	0.066
Previous MoM Growth	-0.12866	0.17496	-0.7353	0.476
Video Length	-6.11e-4	0.00615	-0.0993	0.923
Total Comments	0.00294	9.09E-04	3.231	0.007
Sentiment Score	0.28265	0.02089	13.532	<.001

Table 5 with the model fit measures (Pearson's correlation coefficient R = 0.991 and Coefficient of determination R² = 0.983) suggests that Model 1 has a powerful linear relationship between the independent variables and the dependent variable Search Volume Change (MoM). The model has a high overall fit. However, among the independent variables, only the sentiment score ($\beta = 0.283$, $p < 0.001$) and total number of comments ($\beta = 0.003$, $p = 0.007$) had a statistically significant relationship with the BSV increase in the subsequent month based on the p values at the standard significance level of 0.05. This suggests that with a rise in 1 sentiment score for the brand campaign, there is a likelihood of 0.283, or a 28.3% increase in BSV

in the subsequent month. Similarly, the number of comments in the video seems to positively impact the overall BSV in the following month, suggesting that greater engagement in the video likely impacts the overall increase in BSV in the short term. The length of the video and previous MoM growth were not statistically significant in predicting the change in BSV in the subsequent month. The Q-Q plot of model 1 is given in Figure. 1, which shows a considerable coherence between the observed and theoretical values, suggests the model's strong capacity to predict change in BSV.

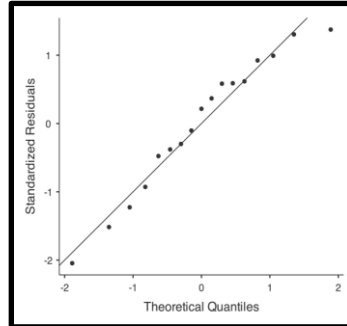


Figure 1. The Q-Q plot for Model 1

Table 1. The OLS regression results for Model 2

Model Fit Measures				
Model	R	R ²		
2	0.974	0.949		
Model Coefficients - Search Volume Change (YoY)				
Predictor	Estimate	SE	t	P
Intercept	-0.0085	0.00684	-1.242	0.238
Previous YoY Growth	-0.093	0.14343	-0.648	0.529
Video Length	1.56E-07	0.0024	6.49E-05	1
Sentiment Score	0.06567	0.00653	10.058	<.001
Total Comments	6.28E-04	3.22E-04	1.949	0.075

Table 6 suggests that only the sentiment score ($\beta = 0.0657$, $p. < 0.001$) had a statistically significant relationship with the BSV increase in the subsequent year. This suggests that with a rise in 1 sentiment score for the brand campaign, a 6.57% increase in BSV is likely in the following year. While the number of comments in the video seems to positively impact the overall BSV in the following year, this statistical significance was not replicated in the BSV change in the MoM period. Similarly, the length of the video and previous YoY growth was statistically insignificant in predicting the change in BSV in the subsequent year.

The model is also a good fit with an R value of 0.974 and an R-squared value of 0.949, suggesting that the model can explain more than 94.9% variance within the dependent variable. The Q-Q plot of Model 2 is given in Figure 2. It shows a considerable coherence between the observed and theoretical values, suggesting a strong capacity of the model to predict change in BSV.

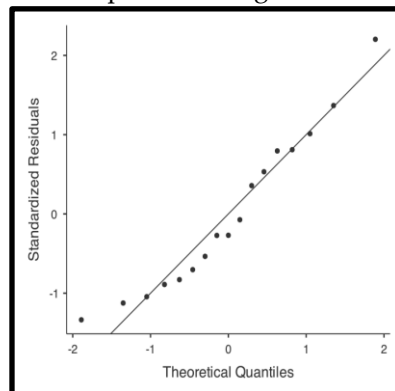


Figure 2. The Q-Q plot for Model 2

4. Discussions

In seeking efficient and reliable methods to evaluate a video branding campaign on social media platforms. We have examined the two most adopted methods, the sentiment analysis after the video brand

campaign and the BSV change on the dominant search engine. Each has particular credibility, but the general understanding is that the sentiment shows the immediate and emotional responses after the brand campaign, and the BSV shows a more reliable and longer-lasting impact. The choice of metric to use practically depends on the campaign objectives and the evaluation timeline. Sentiment is the best choice if the purpose of a video brand campaign is to raise users' awareness and enhance the brand image. If a video brand campaign aims to improve engagement and possible turnover rate, then the BSV may be more reliable. However, the BSV is also affected by many factors such as the popularity and the ease-of-use of the search engine, the inherent fluctuation of the search actions, and most importantly, the search time. Most people agree that combining the two metrics can produce a complete picture of the campaign, but there are cases where the two have produced contradictory results.

Our study finds a strong correlation between the results of the initial sentiment analyses and the BSV shortly after the video campaign was completed and over a more extended period (one year). BSV changes positively correlate with the initial sentiment scores and total comment counts in the subsequent month of the video campaign. The exact positive correlation still exists in the following year, but the effect weakens from 28.3% to 6.57%. Our study particularly confirms that a higher negative-to-positive comment ratio shortly after a brand campaign on YouTube correlates with a decline in BSV in the subsequent month and year. This was reflected by the almost perfect negative correlation between the Neg/Pos Comment Ratio and the MoM (-0.99) and YoY (-0.97). These results provide robust empirical support and reaffirm that sentiment expressed online is not merely reflective of prevalent views that are significant in determining a brand campaign's effectiveness, but also has the potential to serve as a predictive indicator of subsequent behaviours.

The most significant finding of our study is the notable difference from previous research, which has shown negative publicity to have beneficial effects. This research reveals that this phenomenon does not hold for large, well-known brands. Early negativity is a deterrent for these brands, stifling consumer interest rather than piquing curiosity. This suggests that the influence of brand status is essential in mediating the impact of negative sentiment on perception, adding another dimension to existing publicity research. For well-established brands, the immediate reputational damage of negative sentiment is greater, trumping any positive impact of curiosity. This divergence is what necessitates context-sensitive strategies. Established brands cannot take it for granted that all publicity is good publicity; they must recognise their respective vulnerabilities concerning visibility and consumer assumptions and adjust their digital campaign strategies accordingly.

The findings of this study indicate that the link between sentiment and consumer behaviour is complex and context-dependent. Controversy might be advantageous for lesser-known or niche brands, especially if awareness is the main barrier to engagement. Conversely, for well-known mainstream brands, early negative sentiment is detrimental, eroding trust and damaging emotional connections with consumers.

However, our study has limitations that can be addressed in future research. Firstly, VADER, the tool used for analysing social media text, has limitations, particularly its ability to parse sarcasm or humour data. Future studies will consider employing more advanced machine learning models like BERT that better handle social media's informal and unique discourse, like YouTube comment sections. Secondly, data collected from Google Trends are normalised scores rather than the absolute number of BSVs, which can impact OLS estimations. Ideally, we should use absolute values due to the difficulties of obtaining the reliable source data. Alternative or multiple data source should consider for future work. The OLS models are also limited in mitigating the confounding factor. It is advised to add more control variables such as brand annual advertising spend (sourced from Statista) and industry sector (categorical variable: tech, consumer goods, etc.) and even considering use behavior variables like actual purchasing or customer turnover rate. We tolerated the limitation of OLS primarily because it was not used for predicting BSV but to explore the potential relationships. To better predict the BSV change, better machine learning models can be deployed to incorporate more critical factors such as inflation, market growth, brand awareness, etc. Lastly, a larger data sets was desired but not available. It is definitely a hope that use a larger dataset covers more diverse organisation sizes (like medium and small). While analysing the two most adopted metrics for brand campaign evaluation, we contend that user purchase behaviour changes may be the ultimate metrics for evaluating a brand campaign.

5. Conclusion

This paper investigates the relationship between consumers' initial sentiment toward brand campaigns and subsequent changes in consumer search behaviour to identify credible and accurate methods for assessing branding campaign performance. The research established that BSV changes exhibit a strong positive correlation with sentiment scores and total comment counts in the subsequent month and year by utilising a structured approach that integrated sentiment analysis and behavioural monitoring. In addition, our study also confirms that a higher negative-to-positive comment ratio tends to correlate with a decline in BSV following campaign launches. This outcome underscores the significance of digital sentiment as an early predictor of broader consumer engagement, especially for large, established brands. Empirically, the study drives home the value of integrating sentiment data with behaviour metrics. In studies, much of the previous literature has bifurcated online sentiment and behaviour-based outcomes (e.g., search activity). Combining emotional response measures with behaviour-based metrics can better measure campaigns' effect on consumers' behaviourally and attitudinally. This change has considerable implications for the managers and policymakers. Firstly, companies should ensure that their brand campaigns avoid controversy and implement real-time monitoring to respond to the digital sentiment to manage brand value and sentiments and employ corrective actions as necessary. Secondly, policymakers should consider the potential impact of early customer sentiment on brand search behaviour to ensure consumer protection through more transparent and responsible brand communications. Lastly, while sentiment scores provide a snapshot of public sentiment, they must be integrated with comprehensive engagement metrics (e.g., purchases) to assess campaign success honestly. By combining sentiment analysis with visibility metrics, marketers and researchers can better understand audience interaction with and response to digital advertising.

CRedit Author Contribution Statement

Gangmin Li: Data curation, Formal analysis, Writing – original draft, review and editing.

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